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Zhuocheng Ying
Xusheng Cheng
Dongjie Situ
Tian Ruan
Chao Gao
gaoqinchao1@163.com

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Digital Expressions of Sense of Place at Cultural Heritage Sites in Ningbo on Social Media

Zhuocheng Ying[1], Xusheng Cheng[1], Dongjie Situ[1], Tian Ruan[1,2], Chao Gao[1,2]

[1] Department of Geography and Spatial Information Techniques, Ningbo University, Ningbo 315211, Zhejiang, China

[2] Donghai Academy, Ningbo University, Ningbo 315211, Zhejiang, China

E-mail: gaoqinchao1@163.com

Abstract: Social media captures expressions of sense of place at cultural heritage sites, yet cross-platform differences and spatial associations remain unclear. We analyzed 100,083 social media texts from Douyin (TikTok in China) and Weibo covering 78 heritage sites in Ningbo, China. We constructed the Gaze Bias Index, Function Shielding Index, and Platform Sentiment Resonance to characterize these expressions, using empirical Bayes smoothing, kernel density estimation, and optimal-parameter geographical detector analysis to examine spatial patterns and associated factors. Results showed: (1) Douyin emphasized visual expressions and emotional interaction, whereas Weibo emphasized historical narratives, with functional information prominent on both platforms. (2) Sites comprised four types with distinct spatial patterns. (3) Historical depth best explained visual–historical orientation, while commercial density, transportation conditions, and historical attributes explained variations in functional information. These findings connect expressions of sense of place with spatial contexts and provide a quantitative framework for heritage research and governance.

Introduction

Cultural heritage embodies historical information, collective memory, place identity, and sociocultural values. It provides an important spatial foundation for human–place relationships and the continuity of local culture. Heritage research has expanded from the preservation of physical fabric to the social construction of heritage values, with the public helping to shape heritage meanings through observation, use, and narration[1]. Sense of place is an integrated structure of meanings formed through individuals' or groups' interactions with particular places, encompassing spatial experiences, place memories, identity, emotional attachment, and functional connections[2]. Heritage sites provide the material foundation and cultural context for sense of place. Public perceptions and expressions, in turn, influence how heritage values are socially recognized and culturally interpreted, as well as how people participate in conservation.

Digital media have expanded opportunities for the public to express heritage experiences and participate in the production of place meanings[1]. Social media platforms such as Weibo and Douyin enable users to record and share place experiences through text, images, short videos, comments, and reposts[3]. User-generated content (UGC) captures public perceptions, emotional responses, and visitor experiences of architectural heritage, historic districts, and cultural landscapes, making it a valuable source of data for studying public perceptions of heritage[4]. Heritage communication is also closely related to audience engagement and interaction[5]. In this study, we examine the digital expressions of sense of place through observable place-related expressions on social media, focusing on the relative prominence of visual appreciation, historical narratives, functional experiences, and emotional interaction. These expressions capture selected aspects of sense of place

rather than the concept as a whole.

Previous studies have used aspect-based sentiment analysis[6], interpretable machine learning[7], multi-source data fusion[8], and social network analysis[9] to examine visitor experiences, public perceptions of heritage value, heritage communication patterns, and management needs. Platform content-ranking mechanisms, engagement metrics, and information-distribution mechanisms influence the reach and visibility of heritage content[10,11]. Douyin's short-video format emphasizes landscape presentation, photo-taking and location-based sharing activities, and immediate experiences[12], whereas Weibo's textual narratives and topic aggregation facilitate historical interpretation and the sharing of place memories. These platform characteristics may contribute to differences in how heritage is expressed across platforms. Heritage-related UGC also contains functional information about transportation, reservations, ticketing, parking, queuing, and visitor facilities. Such information records how the public accesses, uses, and evaluates heritage spaces, making it an integral part of place experience. A site's historical depth, locational context, transport accessibility, commercial services, and recreational environment also influence public activities and evaluation priorities[2,13,14]. Spatial studies have further documented the distribution patterns and associated factors of intangible cultural heritage along the Grand Canal[15,16], traditional villages[17], and other cultural resources.

Three gaps remain. (1) Systematic comparisons of heritage-related semantics across social media platforms are limited, leaving the relationship between platform characteristics and the visibility of place meanings unclear. (2) Visual appreciation, historical narratives, and functional information have generally been studied separately. Their relative prominence within a shared structure of expression remains insufficiently examined, as does the relationship between textual

sentiment and user interactions such as likes, comments, and reposts. (3) UGC research focuses primarily on online text and user emotions, whereas spatial research emphasizes the distribution of physical heritage resources. An integrated framework linking online semantic representations with historical attributes, transportation, and commercial environments is still needed.

Using cultural heritage sites in Ningbo as a case study, we examine how sense of place is digitally expressed through social media-based place-related expressions and how these expressions vary across space. We address three questions: (1) How do Douyin and Weibo differ in visual–historical orientation, the prominence of functional information, and emotional interaction? (2) What types of digital expression emerge across heritage sites, and how are they distributed and clustered in space? (3) How do site attributes and urban environmental factors such as historical depth, commercial density, and transportation conditions explain spatial differences in these expressions, both individually and through their interactions?

This study makes three contributions. (1) We developed the Gaze Bias Index (GBI), Function Shielding Index (FSI), and Platform Sentiment Resonance (PSR) to characterize observable dimensions of digital expressions of sense of place at cultural heritage sites. These indicators capture visual–historical orientation, the relative prominence of functional information, and engagement-weighted sentiment, respectively. (2) We combined empirical Bayes smoothing[18] with a two-step classification strategy to identify four representation types—landscape consumption, historical narrative, hybrid perception, and function shielding—and analyze their spatial distributions. (3) We combined indicator-weighted kernel density estimation (KDE)[19] with the optimal-parameter geographical detector (OPGD)[20] to integrate online semantic representations with heritage-site historical attributes and urban environmental factors within a unified analytical framework. This

framework was used to examine spatial heterogeneity in digital expressions of sense of place and the explanatory power of individual factors and their interactions. Overall, this study integrates multidimensional semantic indicators with spatial analysis for social media research on cultural heritage.

The research framework comprises four components (Fig. 1): (1) site selection, data collection from both platforms, and text preprocessing; (2) construction of visual, historical, functional, and emotional semantic indicators and calculation of GBI, FSI, and PSR; (3) identification of heritage perception types and spatial patterns using a two-step classification method; and (4) examination of spatial factors associated with digital expressions of sense of place and discussion of their implications for heritage governance.

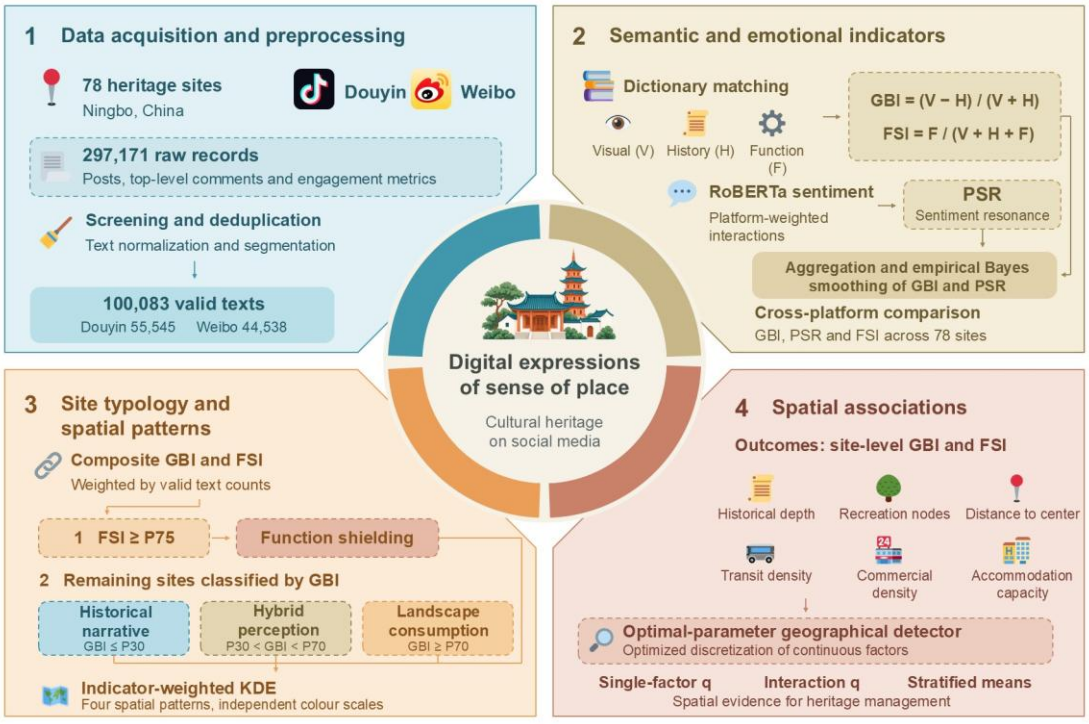


Fig. 1 Research framework and workflow for analyzing digital representations of sense of place at heritage sites.

Methods

Study area, heritage site samples, and data sources

Ningbo, on China's southeastern coast, lies at the intersection of the Maritime Silk Road, the Zhedong Canal system of the Grand Canal, and Jiangnan regional culture[21]. Its heritage sites combine deep historical roots with active tourism and sustained online visibility. The sites include ancient towns, historic districts, religious buildings, former residences, archaeological sites, and scenic landscapes, spanning different historical periods and cultural or natural settings. Given the study design, we selected 78 cultural heritage sites in Ningbo that had sufficient and identifiable social media presence for cross-platform analysis (Fig. 2).

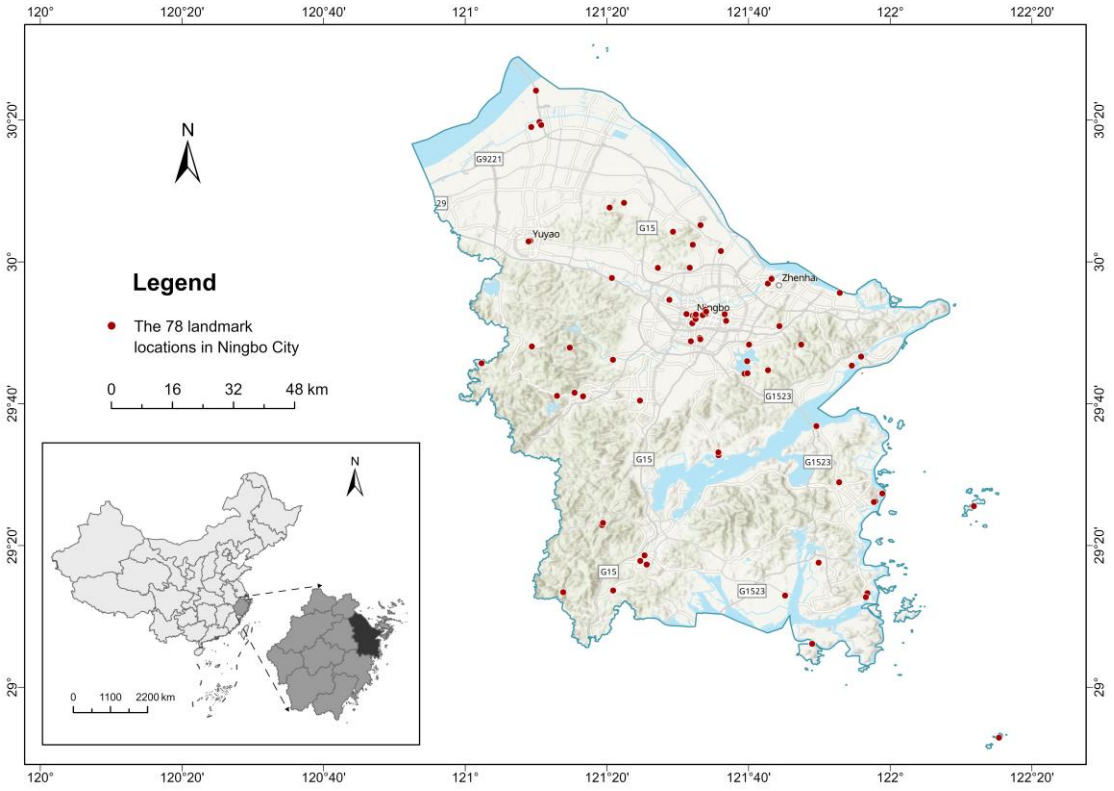


Fig. 2 Locations of the 78 heritage sites in Ningbo.

Social media data were collected from Douyin and Weibo, with platform-specific datasets

retained for subsequent cross-platform comparisons.

We selected heritage sites with a stable and identifiable online presence. Selection criteria included the searchability of site names, sustained representation on both platforms, and the feasibility of cross-platform comparison. Accordingly, the analytical sample represents heritage sites with sufficient online visibility for social media-based comparison rather than the complete heritage inventory of Ningbo. Sites were further classified as cultural or natural according to their landscape attributes. Publicly accessible posts and top-level comments related to 78 heritage sites in Ningbo were collected from Douyin and Weibo using keyword-based searches in MediaCrawler, with each heritage site name used as a search term. Collected fields included textual content, platform source, publication time, and engagement metrics, including counts of likes, comments, reposts, and shares. In total, 297,171 raw records were obtained. After field standardization, text normalization, removal of invalid and low-information records, screening for relevance to heritage and tourism, duplicate removal, and cross-platform comparability checks, 100,083 valid text records covering all 78 heritage sites were retained, including 55,545 from Douyin and 44,538 from Weibo. User identifiers were retained temporarily for duplicate detection and removed before the final analytical dataset was generated. Usernames, profile images, and other profile information were not included in the analytical dataset (Supplementary Tables S1 and S2).

Text preprocessing and sentiment identification methods

To make the cleaned social media texts comparable across sources, we standardized data fields, segmented Chinese text, extracted semantic features, and identified sentiment. We first standardized textual content, platform-source fields, and engagement variables, including likes, comments, and

reposts. The source field was then used to identify each record's platform and content type. Chinese word segmentation was performed with jieba and a custom dictionary to improve recognition of heritage-related terms and colloquial expressions in short texts.

Table 1 Semantic and sentiment dictionaries for heritage-related social media text analysis

Dictionary category	Number of terms	Example terms	Purpose
Visual-related terms	100	photogenic, photography, shooting position, composition, light and shadow, cinematic quality, stunningly beautiful, night view, atmospheric appeal, Hanfu, social-media check-in, internet-famous, recommendation, relaxed ambience, …	Identify landscape presentation, photography and location-based sharing, and aesthetic expressions; used to calculate GBI
Historical narrative terms	101	history, culture, historical depth, cultural continuity, heritage, intangible cultural heritage, cultural relics, archaeological sites, former residences, historical allusions, historical records, archaeology, Maritime Silk Road, …	Identify expressions of historical knowledge, cultural memory, and heritage interpretation; used to calculate GBI
Functional information terms	77	tickets, reservations, queuing, transportation, parking, metro, bus services, navigation, visitor guides, opening, closure, services, facilities, restrooms, crowding, large crowds, …	Identify practical information about transportation, reservations, services, facilities, and visitor arrangements; used to calculate FSI
Fine-grained emotion terms (extended dictionary)	122	awe-inspiring, spectacular, awe, happiness, emotionally restorative, curiosity, informative, disappointment, avoidance warning, crowding, nostalgia, childhood memories, memories of the old days, everyday vitality, …	Cover five emotion categories: awe, pleasure, curiosity, disappointment, and nostalgia; support interpretation of emotions in digital expressions of sense of place

The custom dictionary was developed from the study's sense-of-place indicator framework and comprised three semantic categories. Visual terms were used to identify landscape presentation,

photo-taking and check-in experiences, and aesthetic expression. Historical narrative terms were used to identify historical knowledge, cultural memory, and heritage interpretation. Functional information terms were used to identify practical content related to transportation, reservations, ticketing, queuing, services, and visitor logistics (Table 1). Dictionary-based matching was then used to calculate the frequencies of visual, historical narrative, and functional terms, which served as the basic variables for subsequent calculation of GBI and FSI.

In addition to the three core semantic categories, we developed an extended emotion dictionary to characterize affective expressions in social media texts. It covered five fine-grained emotions: awe, joy, curiosity, disappointment, and nostalgia. These emotion variables were not used to construct the core spatial indicators but were retained as supplementary information for interpreting affective responses. The visual, historical narrative, functional, and emotion categories captured expressions related to landscape appreciation, historical interpretation, visitor services, and emotional responses (Fig. 3). The predefined dictionary terms showed broad coverage across the corpus, with most terms being observed in the collected texts (Supplementary Data 1).

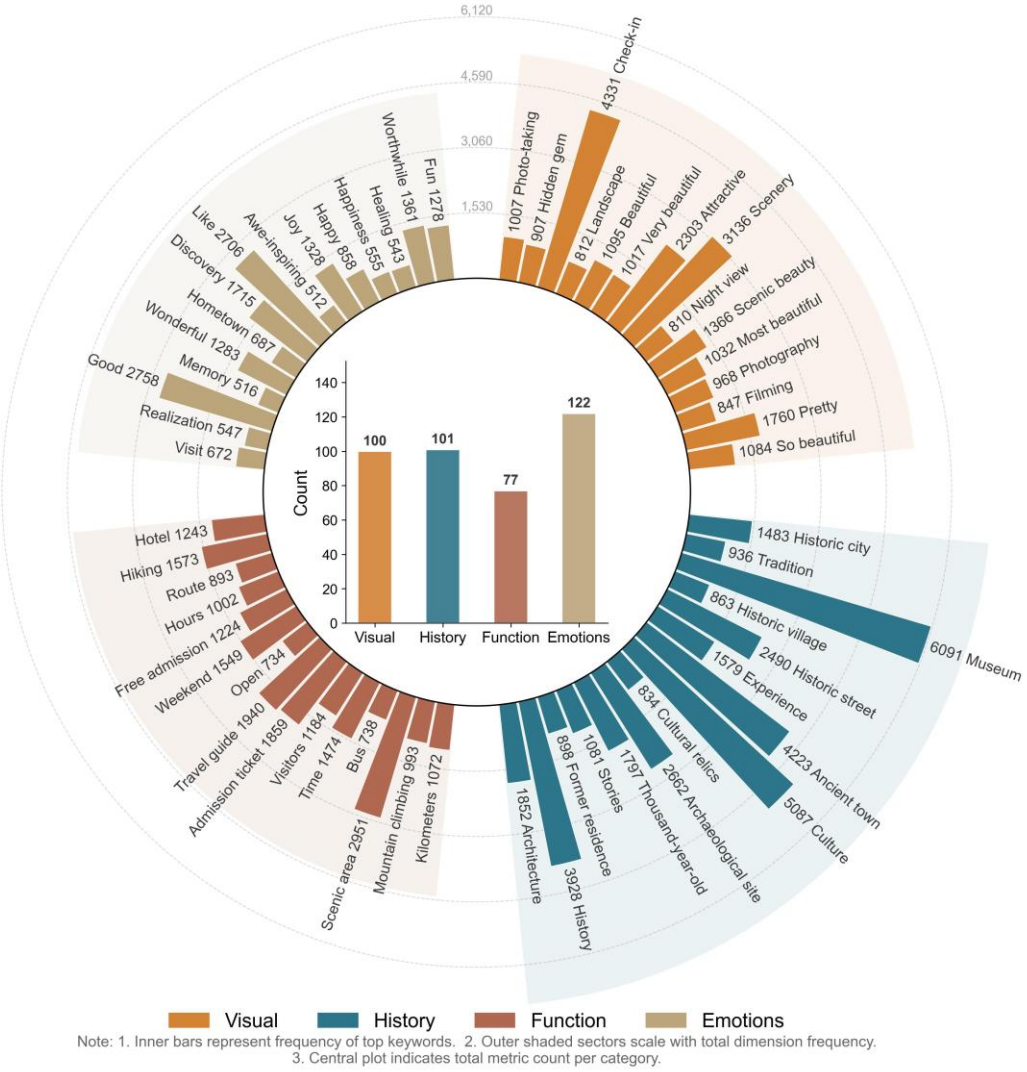


Fig. 3 Frequency distribution of semantic and emotion dictionary terms in the heritage-related social media corpus (top 15 terms by frequency in each dimension).

Sentiment identification was performed using the publicly available **uer/roberta-base-finetuned-dianping-chinese** checkpoint through the Hugging Face Transformers pipeline. This checkpoint is a Chinese RoBERTa-based sentiment classification model fine-tuned for binary sentiment classification on Chinese review texts[22]. The cleaned social media texts were directly input into the model for inference.

The model outputs a predicted sentiment category and its corresponding probability. These outputs were transformed into a continuous sentiment polarity score (s) ranging from −1 to 1:

$$s = \begin{cases} 2p - 1, & \text{predicted positive} \\ 1 - 2p, & \text{predicted negative} \end{cases} \quad (1)$$

where p represents the probability assigned to the predicted sentiment category. Positive and negative values indicate model-inferred positive and negative sentiment tendencies, respectively, whereas values close to zero indicate weaker sentiment polarity.

Before inference, texts containing fewer than two characters after removing leading and trailing whitespace were excluded. Cases in which sentiment inference failed were removed from subsequent analysis rather than assigned a neutral value, because prediction failure does not necessarily represent an intermediate sentiment state. The resulting sentiment scores were used as the basic variable for calculating the Platform Sentiment Resonance index and subsequent spatial analyses.

Construction of the Gaze Bias Index, Function Shielding Index, and Platform Sentiment Resonance

Based on dictionary matching, we calculated the frequencies of visual terms (V), historical narrative terms (H), and functional information terms (F) for each text and constructed three core indicators.

The Gaze Bias Index (GBI) was developed to measure the relative dominance between visual expressions and historical narratives, defined as:

$$GBI = \frac{V - H}{V + H} \quad (2)$$

In the equation, V represents the number of visual terms in a text, and H represents the

number of historical narrative terms. $GBI > 0$ indicates that the text is more oriented toward visual appreciation and landscape consumption, whereas $GBI < 0$ indicates a stronger tendency toward historical narratives and cultural interpretation. Higher values indicate stronger visual landscape orientation, while lower values indicate stronger historical narrative orientation. When V+H=0, the text is classified as lacking visual–historical signals. Such texts are excluded from text-level GBI calculations but retained for sentiment identification, functional information identification, and text volume statistics.

The Function Shielding Index (FSI) was developed to quantify the relative prominence of functional information in digital expressions of sense of place:

$$FSI = \frac{F}{V + H + F} \tag{3}$$

In the equation, V represents the number of visual terms in a text, H represents the number of historical narrative terms, and F represents the number of functional information terms. A higher FSI value indicates a greater proportion of functional information, such as transportation, reservations, ticketing, queuing, services, and travel guides, with a lower relative contribution from visual or historical-cultural expressions.

The Platform Sentiment Resonance (PSR) was developed to characterize the association between emotional expressions and platform interaction intensity. At the individual-text level, a platform interaction score (Interaction Score, IS) was constructed. Considering that Douyin and Weibo exhibit different interaction mechanisms, PSR was calculated separately for each platform before cross-platform comparison. Weighted interaction counts were log-transformed to reduce the influence of highly engaged posts; site-level PSR values were subsequently smoothed using platform-specific means. Likes were regarded as basic attitudinal feedback, comments as active

expressive engagement, and reposts/shares as indicators of further content dissemination. Therefore, platform-specific interaction weights were predefined according to the functional roles of different interaction behaviors. For Douyin posts, which are primarily characterized by short-video diffusion and content redistribution, higher weights were assigned to reposts:

$$IS_{raw}^{Douyin} = 1 \times likes + 2 \times comments + 5 \times shares \quad (4)$$

For Weibo posts, which place greater emphasis on topic discussions and public expression, higher weights were assigned to comments:

$$IS_{raw}^{Weibo} = 1 \times likes + 5 \times comments + 3 \times shares \quad (5)$$

The robustness of the predefined interaction weights was further assessed using alternative weighting schemes (Supplementary Tables S3–S5 and Supplementary Data 2).

In equations (4) and (5), IS_{raw}^{Douyin} and IS_{raw}^{Weibo} represent the original weighted interaction values of Douyin and Weibo posts, respectively. The subscript raw indicates that these values precede the logarithmic transformation. $likes$, $comments$, and $shares$ represent the numbers of likes, comments, and reposts, respectively. These weights reflect the relative contributions of different platform interactions to emotional dissemination rather than fixed universal parameters. To reduce the influence of extreme interaction values, the weighted interaction values were logarithmically transformed:

$$IS = \ln(1 + IS_{raw}) \quad (6)$$

Based on the above, the PSR of each individual text is defined as:

$$PSR = sentiment \times (1 + IS) \quad (7)$$

In equation (7), $sentiment$ represents the continuous sentiment score ranging from −1 to 1, and IS represents the platform interaction intensity. The term $1 + IS$ is used to retain the baseline

emotional expression of texts without interactions, preventing PSR values from being reduced directly to zero when interaction values are zero. After calculating the text-level PSR, values were further aggregated at the "heritage site–platform" level to characterize the overall emotional resonance of specific heritage sites on corresponding platforms.

Therefore, GBI, FSI, and PSR characterize three observable dimensions of digital expressions of sense of place on social media: visual–historical orientation, functional information prominence, and emotional interaction resonance. These indicators provide the basis for subsequent empirical Bayes smoothing, heritage site-level indicator integration, and typological classification.

Construction of Heritage Site-Level Composite Indicators and Methods for Classifying Heritage Sites

To address the imbalance in text counts across different social media platforms for each heritage site and avoid random fluctuations in indicator values caused by small sample sizes, empirical Bayes smoothing[18] was introduced for calibration before calculating the multi-platform composite indices.

For the Gaze Bias Index, smoothing was based on the proportion of visual expressions, and the calibrated index (GBI_{EB}) was defined as:

$$GBI_{EB} = 2 \times \frac{V + \mu_{gaze}\kappa}{(V + H) + \kappa} - 1 \tag{8}$$

In equation (8), V and H represent the frequencies of visual terms and historical narrative terms, respectively, within each "heritage site–platform" unit; μ_{gaze} represents the overall prior proportion of visual expressions on the corresponding platform, and κ represents the semantic prior strength.

For Platform Sentiment Resonance, smoothing was directly applied to the aggregated raw resonance values. The calibrated resonance index (PSR_{EB}) was defined as:

$$PSR_{EB} = \frac{n}{n+\tau} PSR_{raw} + \frac{\tau}{n+\tau} PSR_{platform} \quad (9)$$

In the equation, n represents the number of valid texts within each unit; PSR_{raw} represents the original mean resonance value before smoothing; $PSR_{platform}$ represents the overall mean resonance of the corresponding platform; and τ represents the prior strength for sentiment smoothing. In this study, the prior parameter κ and the mean parameter τ were set to an intermediate strength of 10 to balance controlling random errors in small samples with retaining differences among heritage sites. A sensitivity analysis was also conducted by testing κ/τ = 1, 5, 10, and 20. Site-level GBI rankings remained highly consistent across κ settings, as did PSR rankings across τ settings. The four-type classification, which does not use PSR, remained unchanged across κ settings. Thus, the main results were insensitive to the tested prior strengths (Supplementary Table S6 and Supplementary Data 3).

After the platform-level indicators were smoothed, valid text counts from Douyin (n_d) and Weibo (n_w) for each heritage site were used as weights to calculate weighted averages, yielding the heritage site-level composite Gaze Bias Index (GBI_{site}) and composite Function Shielding Index (FSI_{site}):

$$GBI_{site} = \frac{n_d \times GBI_{EB,\ d} + n_w \times GBI_{EB,\ w}}{n_d + n_w} \quad (10)$$

$$FSI_{site} = \frac{n_d \times FSI_d + n_w \times FSI_w}{n_d + n_w} \quad (11)$$

In the equation, $GBI_{EB,\ d}$ and $GBI_{EB,\ w}$ represent the smoothed Gaze Bias Index values for Douyin and Weibo, respectively; FSI_d and FSI_w represent the original Function Shielding Index values for the two platforms.

After the heritage site-level composite indicators were constructed, a two-step rule-based classification framework was applied to identify four perception-based heritage types. In the first step, function-shielding sites were identified: heritage sites with composite Function Shielding Index values (FSI_{site}) at or above the 75th percentile (P75) of the overall sample were classified separately to isolate sites dominated by practical information and reduce their influence on subsequent assessments of semantic orientation. In the second step, the remaining sites were classified according to their composite Gaze Bias Index values (GBI_{site}). Using predefined percentile-based thresholds, sites in the lowest 30% were classified as historical narrative types, those in the highest 30% as landscape consumption types, and those in the middle 40% as hybrid perception types. This operational classification framework provides a reproducible and interpretable approach for characterizing the diversity of public heritage perceptions expressed on social media and supports subsequent analyses of spatial differentiation patterns and associated drivers.

Analysis of Spatial Differentiation and Driving Mechanisms

After identifying the digital expression types at the heritage-site level, we integrated spatial analysis and quantitative attribution methods to examine their spatial patterns and associated factors. Indicator-weighted Gaussian kernel smoothing (KDE) [19] was used to map the spatial intensity of each type. The historical-narrative and landscape-consumption panels display negative and positive GBI_{site} surfaces, respectively. For hybrid perception, a signed GBI_{site} surface was calculated before its absolute magnitude was displayed; the function-shielding surface was weighted by FSI_{site}. The same bandwidth was used for all four types. Positive and negative components of the

surfaces were scaled separately to the observed within-type indicator extrema. Each panel uses an independent color scale, so surface values should be interpreted within panels rather than compared directly across types.

To identify the factors associated with spatial differentiation in GBI_{site} and FSI_{site}, the Optimal-Parameter Geographical Detector (OPGD) was applied for quantitative attribution analysis[20]. The explanatory variables included historical depth (X_1), recreational node scale (X_2), distance to the city center (X_3), public transportation density (X_4), commercial density (X_5), and accommodation capacity (X_6). Historical depth was treated as a categorical variable, whereas the remaining variables were continuous. OPGD automatically determined the optimal discretization schemes for continuous variables by maximizing the q statistic of spatial stratified heterogeneity[20,23]. To improve the reliability of attribution results, strata with fewer than five samples were excluded and Monte Carlo permutation tests were conducted for significance assessment. Interaction detection was further performed to quantify the joint explanatory power of factor combinations[23,24].

Results

Overall Differences in Digital Expressions of Sense of Place Between Douyin and Weibo

To compare digital expressions of sense of place at cultural heritage sites across platforms, we assessed Douyin and Weibo along three dimensions: the Gaze Bias Index (GBI_{EB}), Platform Sentiment Resonance (PSR_{EB}), and Function Shielding Index (FSI) (Source Data 1 and 2).

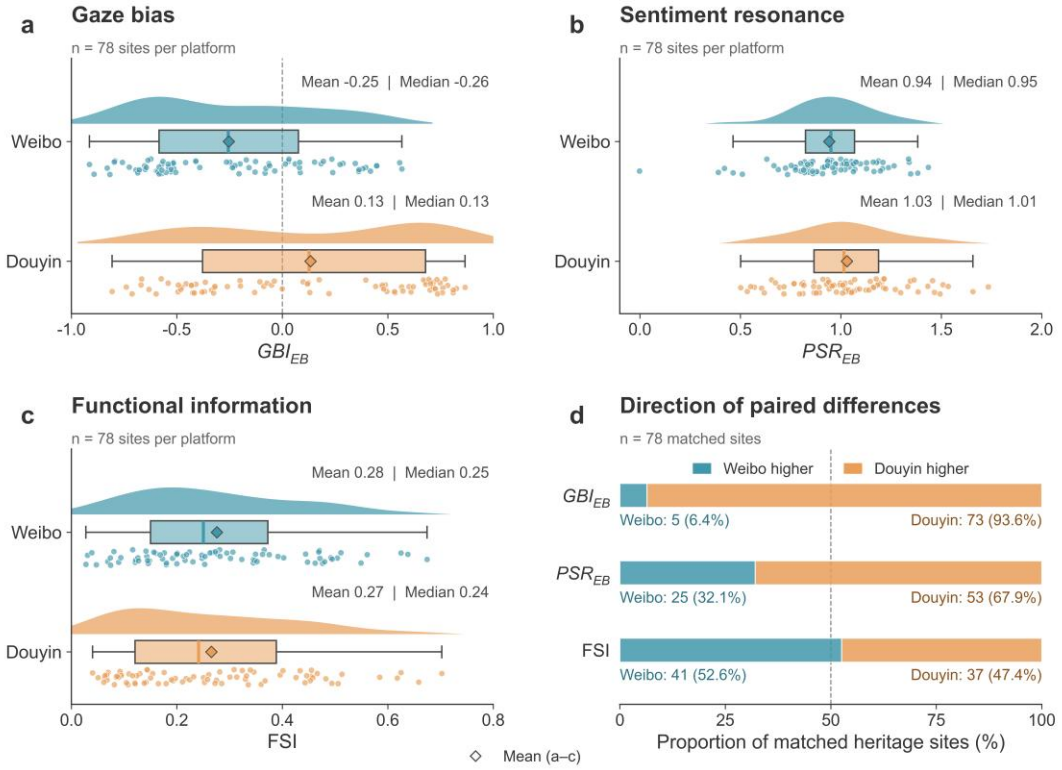


Fig. 4 Cross-platform indicator distributions and within-site comparisons. (a) Empirical Bayes-smoothed Gaze Bias Index (GBI_{EB}); (b) empirical Bayes-smoothed Platform Sentiment Resonance (PSR_{EB}); (c) Function Shielding Index (FSI); (d) proportions of 78 matched heritage sites with higher values on each platform. Curves show kernel density estimates; boxes indicate interquartile ranges and medians; diamonds indicate means; dots represent sites. Panel d describes difference directions, not statistical significance.

The two platforms exhibited distinct differences in gaze orientation toward cultural heritage sites (Fig. 4a). The mean and median values of the smoothed Gaze Bias Index (GBI_{EB}) on Douyin were both 0.13, with values concentrated mainly above zero, indicating an overall tendency toward visual appreciation and landscape consumption. In contrast, the mean and median GBI_{EB} values on Weibo were -0.25 and -0.26, respectively, with values concentrated below zero, reflecting an overall

emphasis on historical narratives and cultural memories. In addition, the wider range of GBI_{EB} values on Douyin indicates greater variability in the degree of visual orientation among heritage sites on the short-video platform.

The two platforms also exhibited structural differences in emotional resonance levels (Fig. 4b). The mean and median values of the smoothed Platform Sentiment Resonance (PSR_{EB}) for Douyin were 1.03 and 1.01, respectively, which were higher than those for Weibo (mean: 0.94; median: 0.95), showing higher engagement-weighted sentiment under the specified scoring scheme. In terms of distribution patterns, Douyin's PSR_{EB} extended toward higher values, whereas Weibo's distribution was more concentrated around its central values.

In contrast to the differences observed in the visual and emotional dimensions, the Function Shielding Index showed similar distributions across the two platforms (Fig. 4c). The mean values of FSI for Weibo and Douyin were highly similar (0.28 and 0.27, respectively), with only minor differences in median values (0.25 and 0.24, respectively). As shown by the probability density plots and boxplots, both platforms exhibited a pronounced right-skewed distribution, with data concentrated in the low-to-medium range and a scattered long tail extending toward higher values. Functional information accounted for a low-to-moderate proportion of expressions at most heritage sites, while only a small number of sites showed pronounced functional information dominance.

The within-site comparison further showed how consistently these cross-platform differences occurred across the sample (Fig. 4d). Douyin had higher GBI_{EB} values at 73 of the 78 heritage sites (93.6%) and higher PSR_{EB} values at 53 sites (67.9%). For FSI, the direction of the difference was more evenly distributed, with higher values on Douyin at 37 sites (47.4%) and on Weibo at 41 sites (52.6%).

Taken together, the multidimensional measurements revealed that the two platforms had distinct structural characteristics in the digital representation of cultural heritage. Douyin showed a stronger orientation toward visual landscape expressions and higher PSR values, whereas Weibo showed a stronger focus on historical narratives. In contrast, the distribution patterns of functional information were similar across platforms.

Digital Representation Types and Spatial Patterns of Heritage Sites

Based on the heritage site-level composite Gaze Bias Index (GBI_{site}) and Function Shielding Index (FSI_{site}), the two-step rule-based classification identified four digital representation types among the 78 heritage sites: function shielding, historical narrative, landscape consumption, and hybrid perception (Fig. 5).

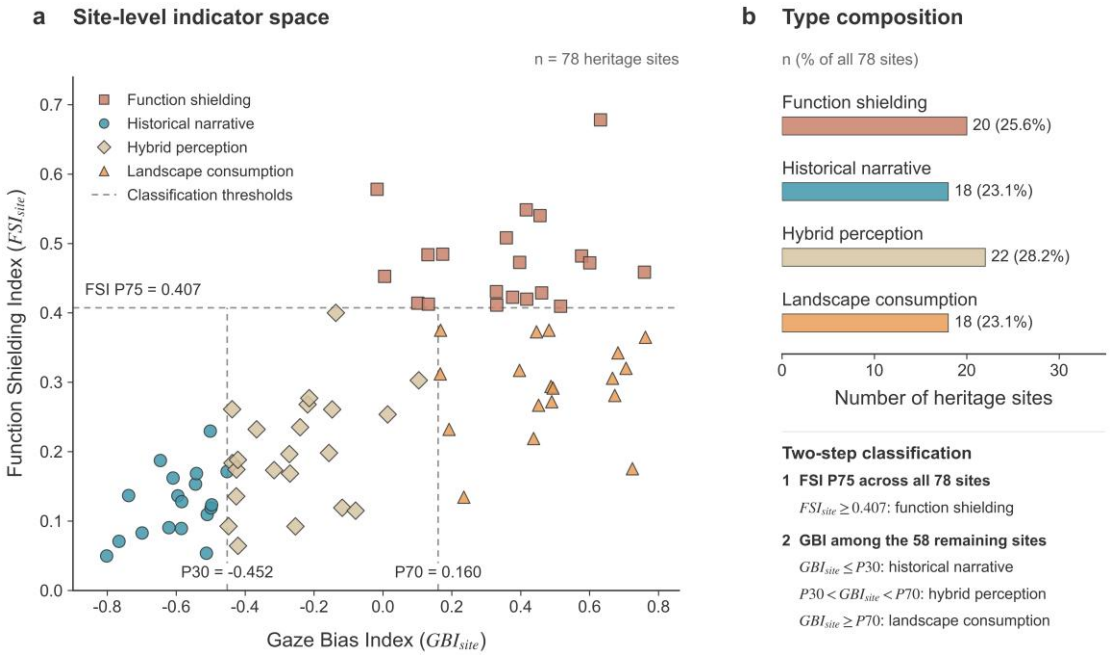


Fig. 5 Digital expression typologies of cultural heritage sites in Ningbo. (a) Site-level GBI–FSI scatter plot with classification thresholds. (b) Counts and proportions of the four types. Sites are first screened by FSI, then classified by GBI.

The 75th percentile of the composite Function Shielding Index (FSI_{site}), calculated across all 78 heritage sites, was 0.407. A total of 20 heritage sites with FSI_{site} values at or above this threshold were classified as belonging to the function-shielding type, accounting for 25.6% of all sites. The remaining 58 heritage sites were further classified according to the relative distribution of GBI_{site} values. The 30th and 70th percentiles of GBI_{site} among these 58 sites were -0.452 and 0.160, respectively. Of these, 18 heritage sites with $GBI_{site} \leq -0.452$ were classified as belonging to the historical narrative type, accounting for 23.1%; 18 sites with $GBI_{site} \geq 0.160$ were classified as belonging to the landscape consumption type, accounting for 23.1%; and the remaining 22 sites between these two thresholds were classified as belonging to the hybrid perception type, accounting for 28.2%.

Four sites illustrate the indicator profiles of the digital expression types. Ninghai National Mountaineering and Fitness Trail had a high FSI_{site} value (0.678) in the function-shielding type; Hemudu Site had a strongly negative GBI_{site} value (−0.802) in the historical-narrative type; Gulou Cultural and Leisure Pedestrian Street had a GBI_{site} value close to zero (0.014) in the hybrid-perception type; and Xiangshan Golden Coastline had a strongly positive GBI_{site} value (0.762) in the landscape-consumption type. Indicator values and semantic characteristics for all eight illustrative sites are reported in Supplementary Table S7.

The four heritage site types exhibited distinct spatial distributions within Ningbo City (Supplementary Fig. S1). Sites of the hybrid perception type were mainly concentrated in the central urban area and its surrounding regions. Sites of the historical narrative type were distributed across

historical nodes in the urban core and peripheral heritage sites. Sites of the landscape consumption type were more frequently located in eastern waterfront areas, scenic areas in the south, and peripheral recreational nodes. Sites of the function-shielding type showed a relatively dispersed distribution across the city, characterized by scattered spatial patterns. In the enlarged map of the central urban area, hybrid perception and historical narrative types were more prevalent, whereas landscape consumption and function-shielding types were relatively few.

The indicator-weighted kernel density estimation results revealed the spatial intensity distributions of the four heritage site types (Fig. 6). Sites of the historical narrative type (Fig. 6a) exhibited a multi-core pattern, with high-value areas mainly distributed along the Yaojiang–Yongjiang corridor, around historical nodes in the central urban area, and near isolated peripheral heritage sites. Sites of the hybrid perception type (Fig. 6b) showed high-value areas concentrated in the central urban area and its surrounding regions, forming a continuous single-core cluster. Sites of the landscape consumption type (Fig. 6c) formed multiple local high-value areas around Dongqian Lake, the eastern coastal zone, and southern recreational nodes. Sites of the function-shielding type (Fig. 6d) displayed relatively dispersed high-value areas, characterized by multiple isolated peaks.

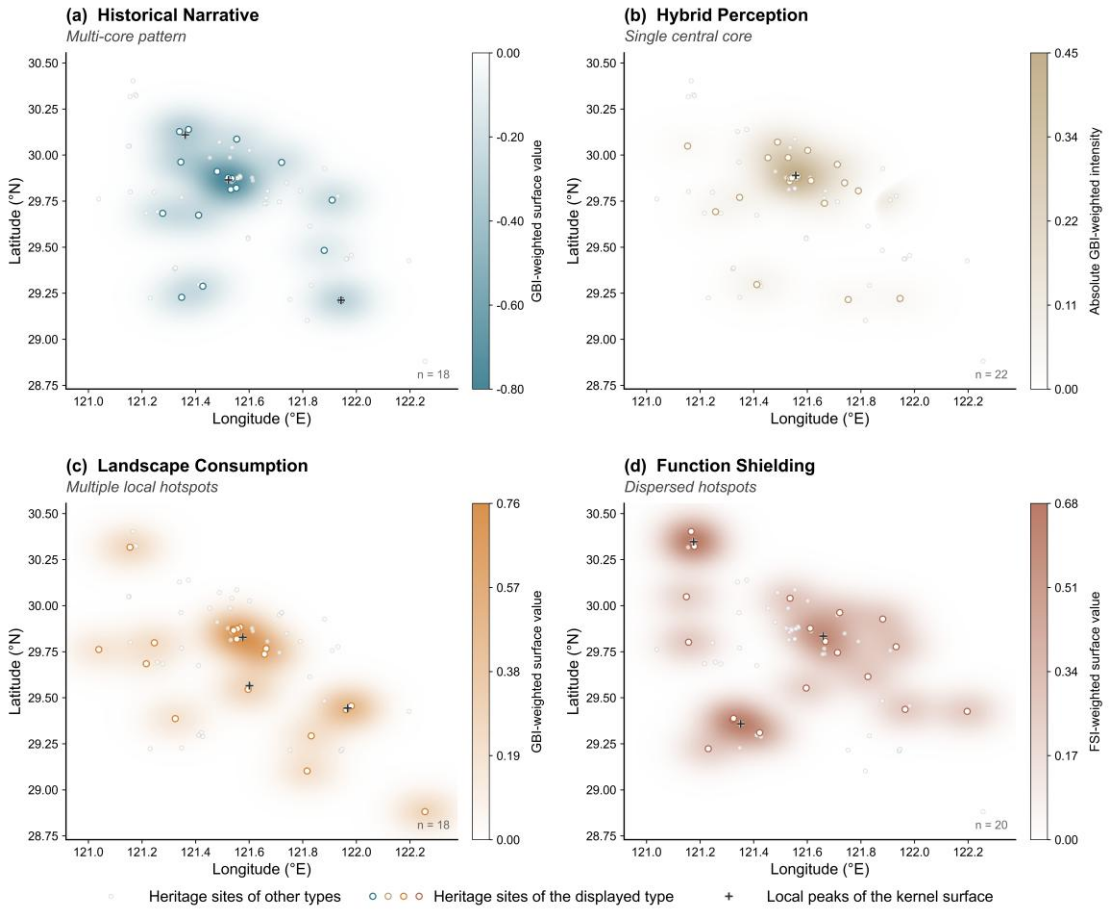


Fig. 6 Spatial concentration patterns of four digital expression types. (a) Historical narrative: multi-core pattern; (b) hybrid perception: single central core; (c) landscape consumption: multiple local hotspots; and (d) function shielding: dispersed hotspots.

The four digital representation types exhibited a spatial pattern combining central clustering, peripheral expansion, and node-based distribution. Sites of the hybrid perception type were primarily concentrated in the central urban area, historical narrative types showed a multi-core distribution pattern, landscape consumption types extended toward waterfront and peripheral recreational spaces, and function-shielding types displayed a dispersed distribution.

To further explain spatial differentiation in the digital expressions of sense of place at cultural heritage sites, we used OPGD to quantify the explanatory power and interaction effects of six spatial factors on FSI_{site} and GBI_{site} (Fig. 7; Source Data 3).

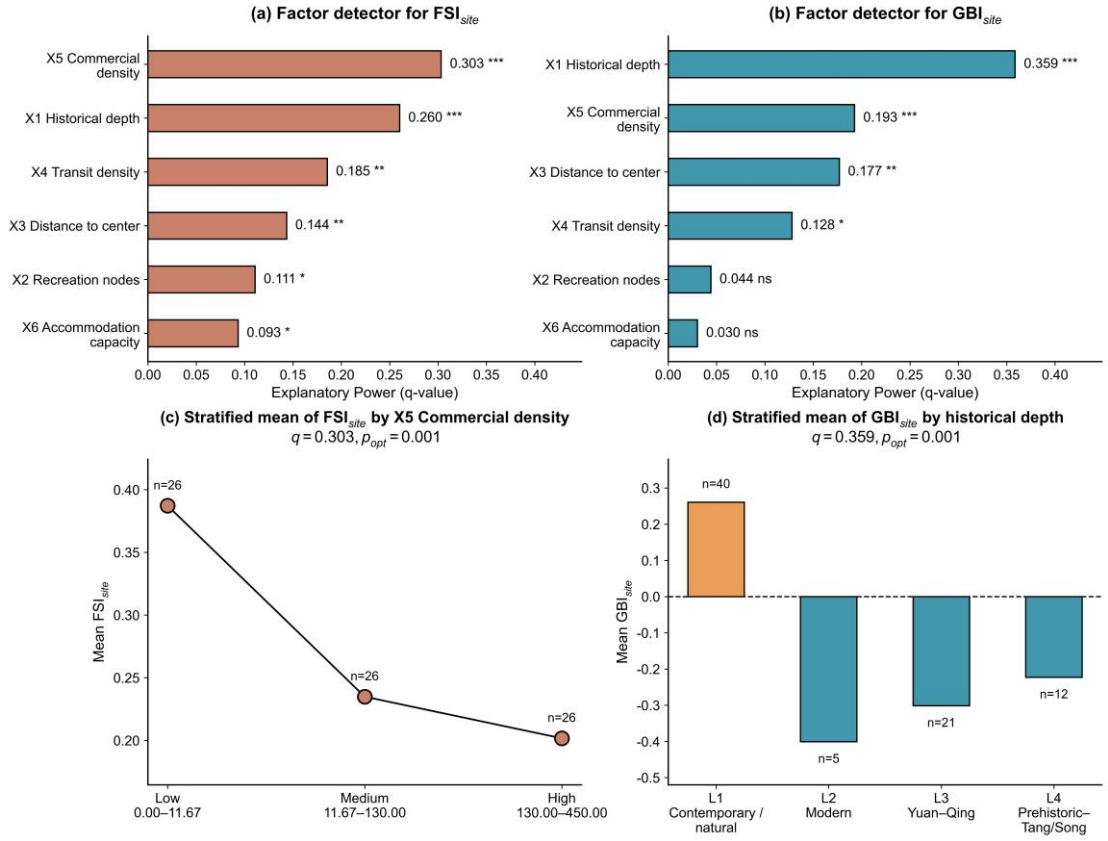


Fig. 7 Explanatory power of spatial factors for FSI_{site} and GBI_{site}. a, b Factor-detector q values for FSIsite and GBIsite, respectively. c Mean FSIsite across commercial-density strata. d Mean GBIsite across historical-depth categories. ***P < 0.01, **P < 0.05, *P < 0.10; ns, P ≥ 0.10.

The single-factor detection results (Fig. 7) showed statistically significant spatial associations between all six factors and variation in the composite Function Shielding Index (FSI_{site}). Commercial density (X_5) had the highest q value ($q = 0.303$), followed by historical depth (X_1,

$q = 0.260$) and public transportation density (X_4, $q = 0.185$). The stratified means (Fig. 7c) showed a consistent decline in FSI_site across the low, medium, and high commercial-density groups, with values of 0.387, 0.235, and 0.201, respectively.

For the composite Gaze Bias Index (GBI_{site}), historical depth (X_1) exhibited the highest explanatory power ($q = 0.359$), followed by commercial density (X_5, $q = 0.193$), distance to the city center (X_3, $q = 0.177$), and public transportation density (X_4, $q = 0.128$). Recreational node scale (X_2) and accommodation capacity (X_6) were not statistically significant. Analysis of stratified means by historical depth (Fig. 7d) further showed that heritage sites in the contemporary or natural category (L1) had mean GBI_{site} values above zero, whereas sites from the modern period (L2), Yuan, Ming and Qing dynasties (L3), and pre-Qin to Song periods (L4), which have a longer historical legacy, exhibited negative mean values. This contrast across historical categories is consistent with the visual–historical orientation captured by GBI.

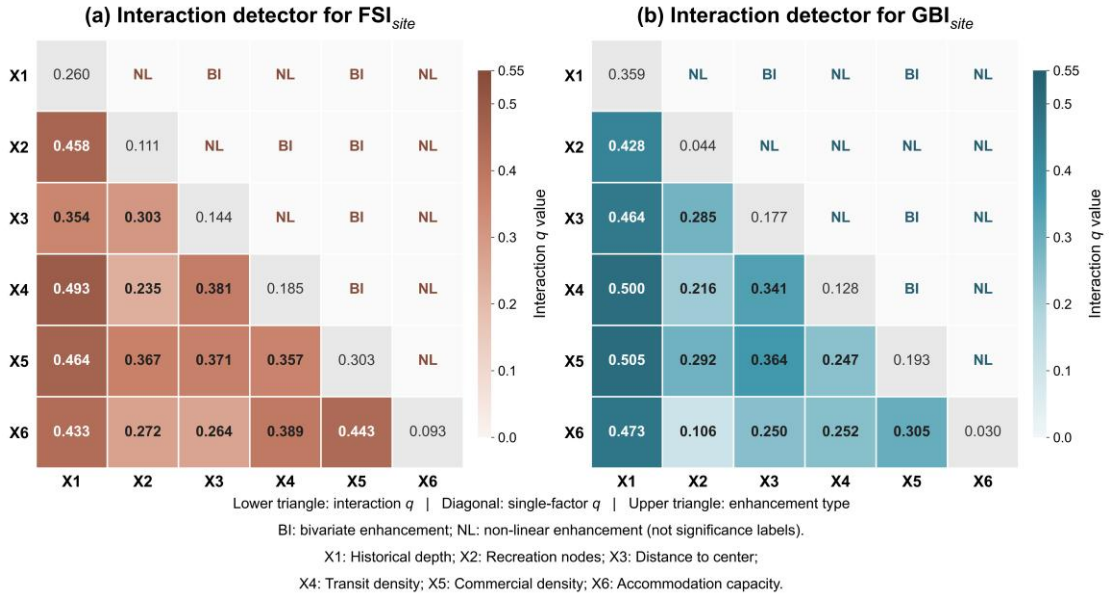


Fig. 8 Interaction-detector results. (a) Interaction effects between spatial factors for FSI_{site}. (b) Interaction effects between spatial factors for GBI_{site}.

The interaction detection results (Fig. 8; Source Data 3) showed that each pair of spatial factors exhibited either bivariate enhancement or nonlinear enhancement effects. For FSI_{site} (Fig. 8a), the interaction between historical depth and public transportation density showed the highest explanatory power ($q(X_1 \cap X_4) = 0.493$), followed by the interactions between historical depth and commercial density ($q(X_1 \cap X_5) = 0.464$) and between historical depth and recreational node scale ($q(X_1 \cap X_2) = 0.458$). For GBI_{site} (Fig. 8b), the top three factor combinations all included historical depth, namely its interactions with commercial density ($q(X_1 \cap X_5) = 0.505$), public transportation density ($q(X_1 \cap X_4) = 0.500$), and accommodation capacity ($q(X_1 \cap X_6) = 0.473$). These results demonstrate that the interactions among physical environmental factors are not simple linear additions, but rather represent a complex synergistic enhancement process in which the historical attributes of heritage sites provide the foundation and interact with other spatial factors.

Discussion

The significant differences between Douyin and Weibo in visual and narrative expressions further support discussions on how platform content organization, distribution mechanisms, and interaction metrics influence cultural content production and visibility, as well as how creators may adjust their expression strategies accordingly[25-27]. Douyin's higher GBI values reflected a stronger visual orientation, which may be attributed to the template-based and easily replicated nature of short-video formats that make similar content more likely to be reproduced[28]. This finding is consistent with previous observations that the dissemination of heritage content on Douyin relies more heavily on visual presentation[12]. In contrast, Weibo showed a stronger emphasis on historical narratives and cultural memories. The comparison between the two platforms further extends

previous descriptions of platform-specific visual and narrative differences by providing a quantitative analysis of the relative balance between visual expressions and historical narratives.

The higher PSR on Douyin indicates that heritage-related emotional expressions receive stronger feedback through user interactions on the short-video platform. Visual elements, music, and editing techniques facilitate the concentrated presentation of experiences such as pleasure, awe, and nostalgia[29], while likes, comments, and reposts further enhance the intensity of interaction around emotional expressions. This finding suggests that image-oriented social media platforms place greater emphasis on observable landscapes and personal tourism experiences in heritage content[30]. It also reflects the simultaneous enhancement of visual expression and emotional interaction. In contrast, the lower PSR on Weibo coincided with its preference for text-based narratives, and the platform did not exhibit the same level of interaction intensity as Douyin. This finding extends discussions on how platform effects influence the visibility of heritage values[31] by incorporating the dimension of emotional feedback and further reveals differences in emotional resonance and interaction intensity across platforms.

The similar distributions of FSI across the two platforms may be attributed to the fact that information related to transportation, ticketing, reservations, opening hours, parking, and service facilities directly supports visitors' travel arrangements, making it less dependent on specific media formats such as videos or text. Compared with previous UGC studies that mainly used such information to identify visitor experiences and management needs[7], this study incorporated functional information into the structure of sense-of-place expression and identified functional shielding in heritage representations based on its proportion relative to visual and historical content.

Compared with previous studies, this study applied consistent indicators to compare Douyin

and Weibo for the same set of heritage sites, reducing the influence of differences in samples and analytical criteria. GBI, PSR, and FSI respectively characterized visual–historical orientation, emotional interaction, and functional information proportions, jointly identifying Douyin's advantages in visual and emotional expressions, Weibo's emphasis on historical narratives, and the stable presence of functional information across both platforms. This framework advances platform comparison research from descriptions of individual content dimensions toward an integrated analysis of digital expressions of sense of place.

Beyond identifying overall differences at the platform level, it is necessary to further compare heritage sites across platforms and examine how visual, historical, and functional expressions combine to form different digital representation types, thereby generating distinct spatial patterns.

The four digital representation types reflected distinct combinations of landscape presentation, historical narratives, and functional experiences, indicating that heritage representations on social media are not shaped by a single dimension. This finding is consistent with the perspective that the social value of heritage is jointly shaped by the resource itself, public experiences, and multi-stakeholder participation[14,32]. The classification of digital representation types was used to identify the dominant modes of heritage expression on social media rather than to evaluate their cultural value or importance.

Landscape consumption, historical narrative, and hybrid perception types exhibited three distinct expression structures based on differences in the proportions of visual expressions and historical narratives. Landscape consumption types were commonly found in waterfront, mountain, and recreational spaces, where strong visual appeal and opportunities for photography facilitated the dissemination of aesthetic impressions, atmospheric experiences, and check-in content on social

media. This extends previous discussions on how experiential quality, perceived authenticity[33], and immersive landscape sharing behaviors[34] influence the visual orientation of heritage content. Historical narrative types drew on clearly identifiable historical periods, figures, events, or archaeological contexts, resulting in stronger expressions of historical knowledge, heritage interpretation, and local memories, and further expanding research on heritage interpretation and value perception[35]. Hybrid perception types combined landscape visibility with cultural content, reflecting the joint influence of heritage resources and visitor experiences on expression structures.

Function-shielding types primarily reflect how heritage spaces are used in practice. Information related to transportation, reservations, opening hours, tour routes, and service facilities is directly associated with visitors' on-site experiences, and functional information tends to occupy a larger proportion of platform texts when such practical issues are emphasized. This finding extends previous UGC-based studies on heritage monitoring and the identification of management needs[6] by further incorporating functional information into the analysis of sense-of-place expression structures. Higher FSI_{site} values indicate that functional content is relatively more prominent than visual and historical content, rather than suggesting a decline in the intrinsic value of heritage sites. Prioritizing the identification of function-shielding types in classification can reduce the interference of functional information with visual–historical orientation assessments.

The spatial differentiation of the four digital representation types corresponded well with the spatial distribution of heritage resources and urban functional configurations in Ningbo. The central urban area brings together historic districts, cultural facilities, commercial services, and transportation networks; here, visual experiences, historical content, and everyday uses overlap, providing a spatial foundation for the continuous clustering of hybrid perception types. Historical

narrative types formed a multi-core pattern consisting of historical nodes in the urban center, surrounding ancient towns, and archaeological sites. Landscape consumption types expanded outward from the central area toward Dongqian Lake, coastal zones, and southern recreational spaces. Function-shielding types mainly appeared as scattered high-value areas around large venues, transportation nodes, and public tourism facilities. These findings extend previous studies on the effects of heritage resources and regional structures on spatial patterns[36,37] to the spatial organization of digital representation types, and correspond with research showing that tourist flows[38], visitor density[39], and social media dissemination[40] can reshape spatial connections among heritage sites. The four spatial patterns not only reflect the distribution of heritage resources but also demonstrate the combined influence of urban functions and public usage patterns on online expressions.

Existing studies have mainly focused on the spatial clustering of heritage resources and the factors influencing it[36,37], or used tourist flows, visitor density, and social media data to depict spatial connections between places[38-40]. This study integrates social media semantics with heritage locations to identify the dominant patterns of visual, historical, and functional expression across different regions. Through the two-step classification approach, heritage sites with high proportions of functional information were first identified, followed by further differentiation based on visual–historical orientation. This approach enables comparisons of central clustering, peripheral expansion, multi-core patterns, and node-based high-value areas from the perspective of digital sense-of-place representation. This extends spatial research on heritage from resource distribution and visitor mobility toward the spatial differentiation of sense-of-place content.

These types and their spatial patterns indicate that digital representations of sense of place exhibit significant regional differences. However, spatial patterns alone cannot explain why these

differences emerge. Therefore, it is necessary to further examine the explanatory power and interaction effects of historical attributes and urban environmental factors.

Historical depth exhibited the highest explanatory power for GBI_{site}. Heritage sites with a richer historical legacy tended to emphasize historical narratives, whereas contemporary or natural heritage sites showed stronger visual orientations. Narrative resources accumulated over time, including historical figures, events, archaeological discoveries, and place memories, provide stable material for public heritage narratives. Building on previous research on the role of heritage interpretation in cultural understanding and memory[41], this study further links historical attributes with the visual–historical orientation of platform texts, indicating that the semantic differences captured by GBI are grounded in identifiable heritage resources.

Commercial density exhibited the highest explanatory power for FSI_{site}, but FSI_{site} decreased with increasing commercial density. This relationship does not indicate that commercialization weakens heritage-related cultural expressions; rather, it may reflect differences in service provision among regions. Areas with higher commercial density generally have more comprehensive transportation, catering, navigation, and public service facilities, reducing visitors' need to discuss practical issues such as routes, parking, and reservations. In contrast, heritage sites with lower commercial density may face fragmented access to information or insufficient visitor support, resulting in a higher proportion of functional content. This finding extends the existing understanding that transportation, services, consumption, and cultural resources jointly influence visitor evaluations[42], further revealing the relationship between urban service environments and the relative proportion of functional information.

Public transportation density and historical depth also showed relatively strong explanatory

power for FSI_{site}. Transportation conditions influence how visitors access and use heritage spaces, while historical attributes provide cultural content for platform narratives. Interaction detection showed that combinations of historical depth with public transportation density, commercial density, and recreational node scale had high explanatory power for FSI_{site}. Similarly, the combinations with high explanatory power for GBI_{site} all included historical depth, together with commercial density, public transportation density, and accommodation capacity. These findings indicate that online heritage representations cannot be explained by a single factor, but rather result from the joint influence of historical resources, accessibility, and the surrounding service environment.

The q value of the Geographical Detector reflects the extent to which explanatory variables account for spatial stratified heterogeneity[23,24]. The bivariate enhancement observed in interaction detection indicates that the power to explain spatial differentiation in GBI_{site} and FSI_{site} further increases when historical attributes are combined with transportation, commercial, and other spatial factors. Historical attributes constitute the core spatial basis for visual–historical orientation, while transportation and commercial conditions jointly explain variations in functional information proportions. The combined effects of multiple physical environmental factors provide a more comprehensive explanation for the spatial differentiation of digital sense-of-place representations.

Historical attributes alone cannot fully explain the online representation of heritage sites; rather, spatial differences in their GBI_{site} and FSI_{site} result from the combined effects of transportation, commercial, and accommodation conditions. This finding extends previous research on the spatial clustering of heritage resources and the spatial structure of tourism activities[38] by advancing the understanding of how online semantic representations are formed. Physical spatial conditions are not only associated with the distribution of heritage resources and visitor activities but are also

associated with differences in how heritage sites are viewed, narrated, and experienced on social media. This complements existing spatial studies of heritage that focus on resource distribution and locational patterns by revealing the spatial differentiation of sense-of-place expressions on digital platforms.

The diagnostic framework also provides practical implications for heritage communication and spatial governance in Ningbo, while offering a basis for adaptation to other cities, heritage types, and social media platforms.

The GBI, FSI, and PSR developed in this study translate visual–historical orientation, functional information proportions, and emotional interaction into comparable heritage site-level indicators, providing quantitative evidence of public expressions for heritage communication and service management in Ningbo. China's 15th Five-Year Plan calls for advancing Digital China development and strengthening the systematic protection of cultural heritage, providing policy support for the use of social media data in heritage monitoring and communication evaluation[43].

In practical applications, GBI can identify whether heritage communication emphasizes landscape presentation or historical narratives, FSI can characterize the functional information structure of heritage-related texts, and PSR can evaluate emotional responses and interaction intensity elicited by heritage content. Together, these indicators provide a dynamic monitoring framework for comparing changes across heritage sites, platforms, and time periods. This application aligns with regional strategies emphasizing the development of high-quality datasets, corpora, knowledge bases, and AI-enabled cultural applications, including the Action Plan for Accelerating the High-Quality Development of the Data Element Market in Ningbo (2025–2027)[44] and the Ningbo "Hundred Scenarios and Thousand Products" AI Empowerment Plan (2026

Edition)[45]. These policies emphasize the development of data resources and AI-enabled cultural applications, and the proposed indicator framework can therefore support the construction of heritage-related social media corpora, the identification of evolving content structures, and the evaluation of communication interventions.

Based on the indicator diagnosis, the four digital representation types correspond to different potential management priorities. Sites of the landscape consumption type already exhibit strong visual appeal, and their photography and check-in content may provide opportunities to further integrate canal culture, maritime culture, and local landscape history. Sites of the historical narrative type show relatively stable cultural expressions and may benefit from approaches such as short-video interpretation, visual timelines, and digital guides to strengthen public engagement. Sites of the hybrid perception type combine landscape presentation with cultural narratives and may provide examples for coordinating online communication with on-site interpretation. Sites of the function-shielding type may require further attention to transportation, reservation, parking, navigation, and service information, as improving these practical service elements could help reduce the dominance of functional information in online heritage communication.

The value of platform indicators for governance lies in identifying features of online expressions that require further verification. When a heritage site shows weak historical narratives, prominent visual expressions, or concentrated functional information, managers can assess the underlying causes by incorporating the perspectives of local communities, visitors, and on-site staff, and then determine whether to strengthen cultural interpretation, improve service information, or adjust participation mechanisms. Community participation[46], authenticity and nostalgic experiences[47], the local social environment[48], and youth participation[49] can all influence the

production and dissemination of heritage-related content. Therefore, diagnostic results should serve as a bridge between platform-based expressions and on-site governance, enabling management measures to respond to the actual needs of specific places and groups rather than simply responding to what is popular on the platforms.

Beyond the Ningbo case, this framework can be extended to World Heritage sites, historic urban areas, cultural landscapes, and archaeological sites, as well as to platforms such as TikTok, Instagram, and travel review websites. However, cross-national applications should not directly adopt the dictionaries, indicator weights, or classification thresholds developed for Ningbo. Differences in language, platform functions, and heritage management systems can affect how heritage values are represented on social media[31]. Accordingly, researchers should reconstruct multilingual semantic dictionaries, adjust interaction indicators, and select spatial variables according to local heritage types and urban environments. After these adaptations, the framework can be used to compare the visual, historical, and functional characteristics of heritage content across different countries and cities.

Overall, digital expressions of sense of place on social media vary with platform characteristics, historical attributes of heritage sites, and surrounding urban environments. Douyin emphasizes landscape presentation and emotional interaction, and Weibo highlights historical narratives, while functional information remains relatively stable across platforms. The four digital representation types exhibit spatial patterns characterized by central clustering, peripheral expansion, multiple cores, and dispersed nodes. By integrating GBI, FSI, PSR, and the two-step classification framework, this study links online semantic structures with offline spatial conditions and provides a basis for differentiated heritage communication and service governance. The study remains limited

by its reliance on textual data, its focus on the Ningbo case, and the associative interpretation of OPGD results. In addition, the requirement for sufficient and identifiable social media presence on both platforms introduces sample-selection bias, potentially underrepresenting heritage sites with limited online visibility. The findings should therefore be interpreted as reflecting digitally visible heritage rather than the full population of heritage sites in Ningbo. Future research should incorporate image and video data, broader sampling frames, multi-city comparisons, and longitudinal analyses to further assess the robustness and transferability of the framework.

Data availability

The datasets generated and analyzed during the current study are not publicly available to protect the privacy of social media users, but are available from the corresponding author upon reasonable request.

Code availability

The underlying code for this study is not publicly available but may be made available by the corresponding author to qualified researchers upon reasonable request.

Abbreviations

UGC	User-Generated Content
GBI	Gaze Bias Index
FSI	Function Shielding Index
PSR	Platform Sentiment Resonance

KDE Kernel Density Estimation

OPGD Optimal-Parameter Geographical Detector

RoBERTa Robustly Optimized BERT Pretraining Approach

BERT Bidirectional Encoder Representations from Transformers

UER Universal Encoder Representations

IS Interaction Score

AI Artificial Intelligence

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Author contributions

Z.Y.: Conceptualization, data curation, formal analysis, methodology, and manuscript writing. X.C.: Conceptual guidance and manuscript review. D.S.: Software guidance. T.R.: Manuscript review. C.G.: Supervision, project administration, and coordination of correspondence. All authors read and approved the final manuscript.

Ethics statement

This study analyzed publicly accessible social media data for academic research. Platform user identifiers were used only for duplicate detection and removed before the final analytical dataset was generated. Subsequent analyses were not conducted at the user level, and no user identifiers are reported.

Competing interests

The authors declare no competing financial or non-financial interests.

Additional information

Correspondence and requests for materials should be addressed to Chao Gao.

Supplementary Files

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- Table1Semanticandsentimentdictionariesforheritagerelatedsocialmediatextanalysis.docx
- SourceData3SpatialfactorsandOPGDresults.xlsx
- SourceData1Primaryplatformsummary.xlsx
- SupplementaryData1Dictionarytermfrequencies.xlsx
- SourceData2Primaryplatformmatrix.xlsx
- SupplementaryData3EBparametersensitivity.xlsx
- SupplementaryData2PSRweightsensitivity.xlsx
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