

Article

Fine-Grained Cultural Perception and Evaluation of Beijing's Capital Culture Integrating Large Language Models with Higher-Order Tensor Decomposition

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Abstract

Fine-grained urban cultural perception is critical for GIScience, yet traditional social media studies struggle with complex cultural semantics and heterogeneous factor integration. Addressing Beijing's "Capital Culture," this study couples LLM agents with higher-order tensor decomposition. Using 2019 full-sample geotagged Sina Weibo data, we developed a four-agent collaborative architecture with Chain-of-Thought prompting and human-in-the-loop mechanisms via a locally deployed Qwen3-32B model. A four-way tensor ("Cultural Type–Evaluation Aspect–Sentiment Polarity–Spatial Carrier") was constructed and integrated with kernel density estimation to characterize spatial differentiation. We address three questions: whether LLMs can reliably classify fine-grained cultural perceptions, how cultural types associate with evaluation dimensions, sentiments, and spatial carriers, and whether tensor decomposition reveals latent patterns beyond marginal frequencies. The agentic workflow achieves over 90% accuracy in cultural and sentiment classification, and the tensor decomposition attains a 94.87% goodness-of-fit, successfully identifying latent patterns. Spatially, Beijing's capital culture exhibits an unbalanced hierarchical structure—"high coupling in the core area with differentiated expansion at the periphery." This study validates the transition from "data-driven" to "AI + data dual-driven" spatial analysis, providing a quantifiable pathway for LLM-supported urban cultural governance.

Keywords: cultural sensing; large language models; agentic workflow; aspect-based sentiment analysis; tensor decomposition; cultural heritage



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1. Introduction

1.1. Research Background and Significance

Culture constitutes the spiritual lifeline of a nation and people, as well as a fundamental driver of urban comprehensive competitiveness and national cultural soft power. In the context of China's advancement of the National Cultural Center construction, the refined governance and effectiveness evaluation of urban cultural spaces have become critical research issues in geography, urban planning, and digital humanities. As a world-renowned ancient capital, Beijing possesses over 3000 years of urban history and more than 860 years as a capital city, making it a representative and analytically valuable case for studying urban cultural systems.

Currently, Beijing's urban cultural heritage can be systematically categorized into four core types: Ancient Capital Culture, Red Culture, Beijing-Flavor Culture, and Innovative Culture [1]. These cultural forms are embedded within diverse spatial carriers, ranging from the Central Axis and historical heritage sites to hutong neighborhoods, revolutionary landmarks, and emerging innovation clusters, collectively shaping a multi-dimensional urban cultural space. Understanding how these cultural types are perceived, evaluated, and differentiated by the public across spatial contexts remains a key yet challenging research issue.

However, cultural perception—defined as the process through which individuals recognize, interpret, and emotionally respond to cultural information [2]—is inherently abstract, multi-dimensional, and spatially heterogeneous. Traditional approaches such as questionnaire surveys and manual sampling are constrained by limited spatial and temporal coverage, making it difficult to capture large-scale, dynamic, and fine-grained cultural perception patterns [3]. In GIScience, the concept of “Social Sensing” provides a new paradigm for extracting human perceptions from large-scale spatiotemporal data [4]. Building upon this perspective, urban cultural perception can be further understood as a data-driven analytical framework for revealing collective cognitive and emotional responses to urban cultural environments.

Despite these advances, accurately capturing fine-grained cultural perception across multiple cultural categories and spatial contexts remains a significant methodological challenge. Existing natural language processing (NLP) methods are often insufficient for handling large-scale, unstructured, and semantically complex cultural data, particularly when multiple dimensions such as cultural type, evaluation aspect, sentiment polarity, and spatial carrier are involved simultaneously. As a result, existing approaches struggle to systematically reveal the intrinsic relationships among these dimensions.

Recent advances in large language models (LLMs), particularly in semantic understanding and contextual reasoning, offer a promising pathway to transform cultural perception analysis from coarse-grained description to structured and fine-grained evaluation. Against this background, this study takes Beijing as a case and utilizes a large-scale dataset of approximately 11.76 million geotagged Sina Weibo posts. By constructing an LLM-based multi-agent analytical framework, this research aims to (1) extract fine-grained cultural perception information, (2) reveal its multi-dimensional spatial patterns, and (3) provide empirical and methodological support for urban cultural governance and cultural spatial optimization.

1.2. Literature Review

1.2.1. Social Media-Based Cultural Perception and Aspect-Level Analysis

The widespread adoption of social media and location-based services (LBSs) has profoundly transformed the dissemination and organization of urban spatial information. As the core carriers through which the public expresses opinions, shares cultural experiences, and records spatial behavioral trajectories in the digital age [5], geotagged social media texts—when combined with recent advances in AI-based urban perception analysis [6]—enable the real-time capture of public attitudes and emotional responses toward cultural entities and geographic spaces. Their openness, high density, and real-time feedback characteristics make them invaluable data resources for conducting social sensing and cultural spatiotemporal mapping. However, when confronted with massive, discrete, low-signal-to-noise-ratio unstructured short texts within social media, how to efficiently extract complex cultural semantics, precisely mine fine-grained emotional information, and achieve spatial positioning constitutes a key technical requirement supporting both academic research and practical decision-making.

Aspect-Based Sentiment Analysis (ABSA), a core research direction within NLP, focuses on identifying and analyzing fine-grained public opinions toward specific topics, entities, and their attributes. Recent reviews have systematically surveyed the methodological landscape of ABSA, highlighting its evolution toward more efficient and multimodal approaches [7]. The granularity evolution of sentiment analysis has progressed from ‘document-level’ to ‘sentence-level’ deepening; driven by deep learning technologies, ABSA has gradually become a research hotspot [8], achieving a technical leap from coarse-grained overall sentiment classification to fine-grained joint judgment of ‘aspect term–sentiment polarity’ [9]. Technically, ABSA tasks can typically be decomposed into Aspect-Category Sentiment Analysis (ACSA) and Aspect-Term Sentiment Analysis (ATSA). As early as 2004, Hu and Liu [10] conducted foundational research on text topic and aspect term extraction based on frequent itemset mining.

Reviewing the historical development, early ABSA research predominantly relied on semantic rules and grammatical dependencies within textual vocabulary. For instance, Poria et al. [11] employed deep convolutional neural networks for aspect extraction from text. More recently, the integration of multimodal reasoning—such as using large language models’ vision capabilities with spatial data [12]—has opened new avenues for contextualized urban perception analysis, moving beyond purely text-based methods. However, purely rule-based and topic-modeling approaches still require substantial manual intervention and struggle to capture long-tail or fine-grained aspect information in domain-specific contexts [13–15].

With the introduction of supervised learning, traditional machine learning algorithms—such as conditional random fields (CRFs) [16] and support vector machines (SVMs) within modular ABSA frameworks [17]—have been applied to sequence labeling and ABSA tasks. More recently, deep learning approaches, including convolutional and recurrent neural networks, have been widely adopted to overcome the limitations of manually engineered features [18]. For instance, Toh and Su [19] employed convolutional neural networks (CNNs) for aspect category extraction; Du et al. [20] further proposed a multiple-CNN approach; He [21] designed a model based on aspect semantics and gated filtering networks, leveraging convolutional layers to overcome temporal dependencies; and Li et al. [22] advanced the application of recurrent neural networks (RNNs) in ABSA tasks. Building on these deep learning foundations, recent studies have further extended the analytical scope by applying LLM-driven approaches to large-scale urban semantic analysis, demonstrating the potential of combining advanced language models with spatial data for urban perception studies [23].

In recent years, the integration of semantic knowledge enhancement with deep learning has opened new directions for this field. Scholars have attempted to combine pre-trained language models [24] with bidirectional long short-term memory networks (BiLSTM) to accomplish joint extraction of ‘aspect term–opinion term–sentiment label’ triples [25], or further integrate external knowledge graphs to significantly enhance the model’s deep understanding of overall sentence structural and semantic information in few-shot or vertical industry scenarios [26]. As research perspectives have extended, ABSA has progressively expanded from traditional unimodal text parsing to the cross-modal collaborative sensing of text, images, audio, video, and other multimodal data.

In summary, existing research has become proficient at leveraging various deep learning and NLP methods to deeply mine users’ multi-dimensional sentiments toward specific attribute targets. However, at the intersection of digital humanities and geoscience big data, when confronting tens of millions of cross-domain heterogeneous multi-source data interwoven with spatial geographic entities, ABSA research still faces novel challenges, including the scarcity of high-quality annotated datasets in specific domains and cross-

domain transfer difficulties. Moreover, the integration of fine-grained spatial semantics with textual analysis remains a critical unresolved issue, as highlighted by recent GIScience–LLM agenda-setting studies [27]. At the same time, the rapid advancement of foundational LLMs [28] offers new opportunities to address these challenges, though their application to spatial-cultural contexts requires careful methodological alignment. This results in traditional approaches that rely on costly manual annotation struggling to simultaneously achieve ‘deep semantic analysis’ and ‘broad geographic coverage’ when addressing complex urban cultural spatial perception problems.

1.2.2. LLMs in Aspect-Based Sentiment Analysis

Building upon the opportunities outlined above, the groundbreaking advances of large language models (LLMs) have provided revolutionary technical opportunities for the low-cost, high-efficiency processing of large-scale unstructured spatial text data. With the successive release of models such as the GPT series [29], alongside comprehensive reviews of LLM applications in geospatial science [30], LLMs—through their massive parameters and pre-trained weights—have demonstrated exceptionally superior general semantic generalization and complex information extraction capabilities under zero-shot or few-shot conditions.

In deep-level applications, LLMs exhibit significant advantages when processing texts with complex cultural contexts, metaphors, and Chinese lexical polysemy. Research has shown that through prompt engineering or domain fine-tuning, LLMs can achieve semantic parsing accuracy and generalization capability comparable to—or even surpassing—fine-tuned traditional medium- and small-scale supervised models such as BERT, without relying on intensive manual annotation [31,32]. This provides a powerful toolkit for mining long-tail evaluation dimensions, fine-grained attributes, and complex emotional mapping networks from massive unstructured texts.

Notably, social media texts inherently often contain geographic location information or implicit spatial entities. Wu et al. [33] proposed a location-weighted attention–cross-attention LSTM aspect-level sentiment analysis model (LWAOA-LSTM), confirming that incorporating geographic location weights significantly improves classification performance compared to traditional text-only models, thereby technically establishing that spatial positional relationships are an indispensable dimension for reconstructing perception evaluation systems. More recently, the integration of multimodal LLMs with street view imagery [34] and the application of LLM-driven approaches to street space perception evaluation have further demonstrated the potential of combining spatial data with semantic analysis for urban perception studies. However, current research that deeply integrates spatial geographic positional relationships with multi-dimensional ABSA frameworks and orients toward specific urban cultural spatial governance remains at an exploratory stage. Furthermore, LLM-based ABSA research targeting Chinese macro-cultural semantics has predominantly focused on algorithmic improvements in model architecture optimization or fine-tuning strategies (e.g., Chain-of-Thought (CoT) [35], Retrieval-Augmented Generation (RAG), etc.), with relatively limited in-depth exploration of the deep integration between social sensing theory and specific cultural geographic application scenarios [36].

This study integrates LLM technology into the ABSA framework by designing a localized agentic workflow supported by Chain-of-Thought (CoT) and self-reflection mechanisms, achieving automated text parsing, automatic identification and alignment of 17 fine-grained evaluation aspects, and spatial POI carriers. This enables cultural evaluation to transcend the traditional ‘positive/negative’ coarse-grained binary judgment and delve into specific spatial elements and experience attribute levels, providing an innovative ex-

ploratory case for GIScience analysis transitioning from the traditional single ‘data-driven’ paradigm to an ‘AI + data dual-driven’ paradigm [37].

1.3. Research Questions

Building upon the identified research gaps and the methodological opportunities afforded by large language models and higher-order tensor decomposition, this study formulates three nested and empirically testable research questions that guide the subsequent methodological design, empirical analysis, and policy discussion:

RQ1 (Technical Feasibility): Can a locally deployed large language model (Qwen3-32B) reliably extract fine-grained cultural perception information at scale? Specifically, this requires: (a) achieving an accuracy of $\geq 90\%$ in four-category cultural type classification (Ancient Capital Culture, Red Culture, Beijing-Flavor Culture, and Innovative Culture); and (b) generating structured ABSA triples in the form of {carrier–aspect–opinion–polarity} that demonstrate substantial agreement (Cohen’s $\kappa \geq 0.60$) with an independent validation model (DeepSeek-V3).

RQ2 (Pattern Differentiation): Do different cultural types exhibit systematically differentiated evaluation profiles? Does the covariance between sentiment polarity and spatial carrier type significantly exceed random expectation—testable via Cramér’s V effect sizes and tensor decomposition—thereby revealing higher-order interaction effects among cultural type, evaluation aspect, sentiment polarity, and spatial carrier?

RQ3 (Interpretability and Actionability): Can CP tensor decomposition at rank $R = 9$ recover interpretable and spatially coherent latent patterns that simpler methods (e.g., LDA topic models and NMF) fail to capture? Furthermore, are these patterns: (a) stable across random initializations, (b) demonstrably superior to matrix-based baselines, and (c) actionable for informing urban cultural governance and spatial optimization strategies?

1.4. Research Content and Innovations

This study is grounded in massive spatiotemporal social media data and fully leverages the synergistic advantages of LLMs and fine-grained ABSA, constructing a perception evaluation technical framework targeting Beijing’s four cultural categories: Ancient Capital Culture, Red Culture, Beijing-Flavor Culture, and Innovative Culture. It deepens the cross-disciplinary integration of GIScience, digital humanities, and urban planning, providing a quantitative pathway for evaluating the effectiveness of National Cultural Center construction. The main research contents are as follows:

Taking Beijing as the study area and relying on approximately 11.76 million original social media text records, this research harnesses the powerful semantic understanding capabilities of LLMs to construct a localized multi-agent workflow supported by Chain-of-Thought prompting and human-in-the-loop mechanisms. Over 270,000 high-quality cross-perception data records are filtered and cleaned, achieving automated cultural type classification, aspect-level sentiment triple extraction, and geospatial entity matching throughout the entire pipeline. Building on this, a higher-order tensor decomposition method is introduced, constructing a four-mode tensor model comprising ‘Cultural Type–Evaluation Aspect–Sentiment Polarity–Spatial Carrier’ ($R = 9$). Integrated with kernel density estimation (KDE) and spatial hotspot analysis techniques, the study systematically characterizes the spatial differentiation features, cross-dimensional transmission mechanisms, and latent perception patterns of capital cultural perception, ultimately forming a deployable, interpretable, and spatially explicit cultural perception spatial intelligence evaluation system.

The main innovations of this study are reflected in the following three aspects:

(1) Construction of a fine-grained capital cultural perception evaluation model, providing precise emotional semantic data sources for GIS spatial analysis. Grounded in social sensing and cultural perception theoretical frameworks, and targeting the differentiated connotation characteristics of four capital culture types, a multi-agent collaborative workflow is designed based on LLM technology to achieve automated, contextualized parsing of massive, complex cultural texts. Seventeen fine-grained perception aspects under each cultural type are precisely identified and quantified, overcoming the limitations of traditional cultural evaluation methods characterized by strong subjectivity, coarse granularity, and difficulty in scaling, injecting fine-grained emotional data streams that integrate both spatial positioning and high-dimensional semantics into GIS spatial analysis.

(2) Realization of deep ABSA-GIS integration for spatial semantic analysis, promoting the transformation of traditional geospatial analysis toward an ‘AI + data dual-driven’ paradigm. A dedicated spatial entity recognition agent is constructed to accomplish automated extraction of material cultural carriers and precise alignment with geospatial POI databases. By deeply binding the fine-grained sentiment triples produced by the LLM with geographic spatial coordinates, the spatial distribution heterogeneity of Beijing’s four cultural perception types is systematically revealed, establishing an integrated evaluation paradigm spanning from textual multi-dimensional semantics to geospatial carriers.

(3) Innovative introduction of higher-order tensor decomposition methods, breaking the single-dimensional constraints of traditional text sentiment analysis and substantially enhancing GIS multi-dimensional coupling feature mining capabilities. The tensor decomposition method is introduced into the research framework of cultural geography and social sensing, constructing a four-mode tensor model comprising ‘Cultural Type–Evaluation Aspect–Sentiment Polarity–Spatial Carrier.’ At a high goodness-of-fit of 94.87%, nine latent cultural perception patterns with clear semantic interpretation and spatial directionality are successfully identified. By cross-dimensionally mapping the higher-order tensor decomposition results onto the GIS platform, a fused expression of textual semantic space and geographic entities is achieved, providing a quantifiable and interpretable new method for urban multi-dimensional, multi-scale refined spatial evaluation.

2. Data and Methods

The overall technical workflow of this study is illustrated in Figure 1, which consists of four core stages: data acquisition, agentic workflow processing, sentiment analysis, and spatial analysis.

2.1. Study Data

This study utilized the web crawler tools (Python 3.3) to systematically collect geo-tagged Weibo posts located within the administrative boundaries of Beijing (Figure 1). The collected data attributes include Weibo ID, text content, posting time, and latitude/longitude coordinates. A full corpus of approximately 11.76 million Weibo user text records from Beijing in 2019 was obtained. After preprocessing and filtering through the agentic workflow (Section 2.2.1), a geo-tagged analytical sample of approximately 277,000 valid records was retained for spatial analysis. The data cover the entire Beijing area with a complete natural year temporal span, possessing strong spatial representativeness and temporal continuity, thereby establishing the data foundation for conducting large-scale cultural perception analysis.

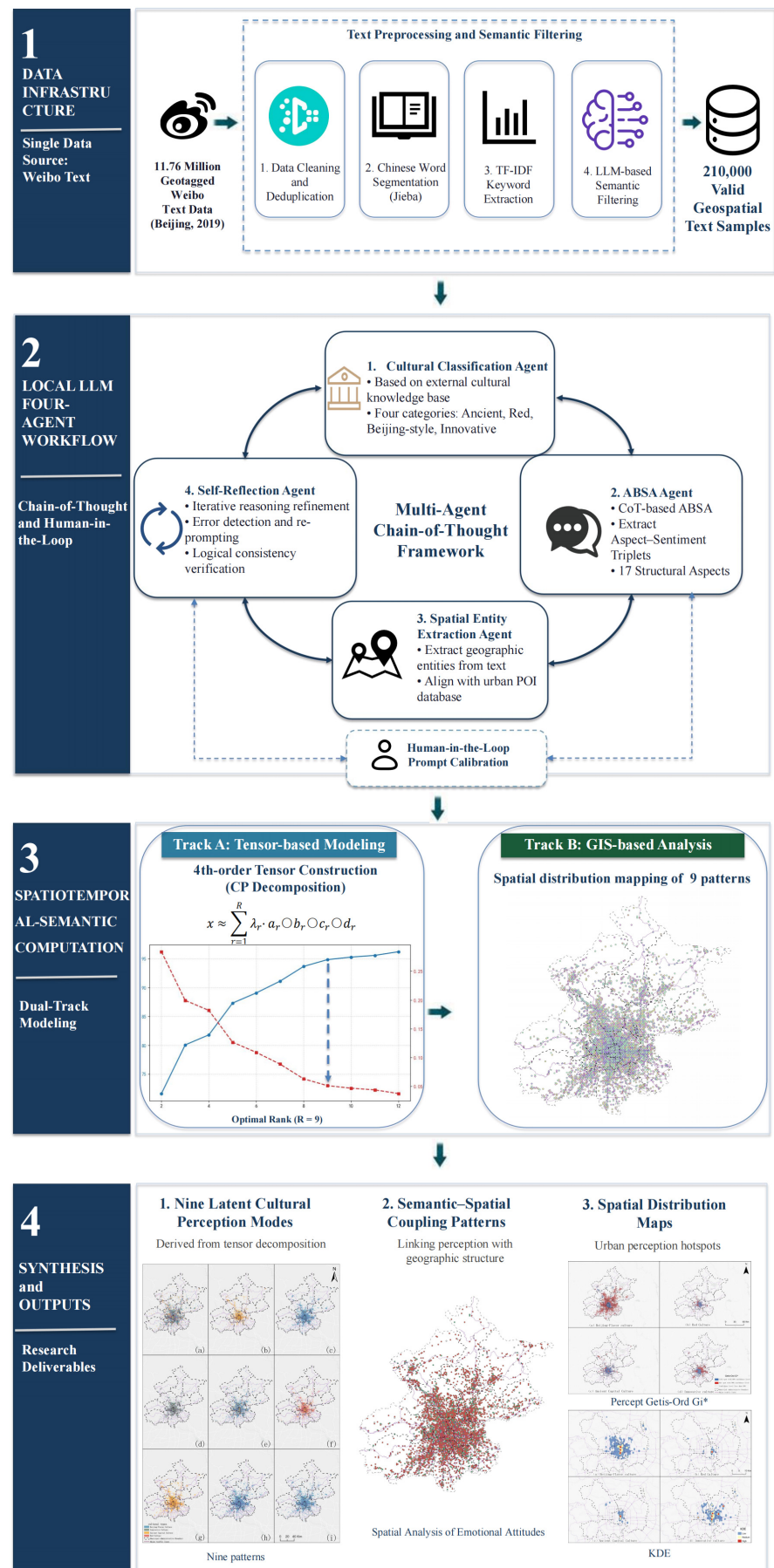


Figure 1. Technical workflow diagram.

2.2. Research Methods

2.2.1. Agentic Workflow

The agentic workflow constructed in this study consists of four core agents, each comprising three fundamental elements: input, context, and output. The prompt, as the core input to each agent, exerts a decisive influence on the final experimental output [37]. This study adopted a Chain-of-Thought (CoT) strategy in prompt design [38], embedding step-by-step reasoning examples within prompts to guide the LLM in conducting explicit reasoning during ABSA tasks, significantly improving the accuracy and consistency of sentiment triple extraction under zero-shot conditions.

Each agent corresponds to a distinct stage of the processing pipeline, with structured data (JSON/Markdown) serving as the cascading transmission medium: (1) Cultural Classification Agent: utilizing a pre-constructed semantic knowledge base of ‘Capital Culture (Ancient Capital, Red, Beijing-Flavor, Innovative),’ this agent performs cultural semantic analysis and type determination on the original text. It is responsible for identifying the cultural type to which the text belongs, providing contextual anchors for subsequent fine-grained analysis. (2) ABSA Agent: employing the Chain-of-Thought (CoT) strategy [38], this agent performs aspect-level sentiment analysis on the text. It deconstructs evaluations into ‘evaluation content–evaluation aspect–sentiment polarity’ triples, achieving the transformation from macro-level sentiment to fine-grained perception aspects. (3) Spatial Entity Extraction Agent: dedicated to identifying and extracting material cultural carriers (entities) related to cultural perception from semantic texts. Through potential alignment with the POI database, it ensures that the extracted carriers possess the foundation for spatial coordinate referencing, addressing the mapping problem between semantic entities and physical spatial entities. (4) Self-Correction and Reflection Agent: serving as the closed-loop component of the workflow, this agent performs sampling inspection on the outputs of the preceding three stages. When the identified ‘material cultural carrier’ exhibits significant logical contradiction with its associated ‘cultural type’ and ‘evaluation content,’ this agent triggers a re-reasoning mechanism, invoking the relevant preceding agents to correct potential judgment errors.

The workflow composed of the above four agents adopts a variable-passing mechanism: the output of each preceding step directly serves as the input variable for the subsequent step, ensuring that the model consistently maintains a continuous ‘reasoning chain’ when processing each data item. Furthermore, to ensure the accuracy of agent task completion, the study introduced a human-in-the-loop mechanism and divided the nearly ten million text records into ten batches for processing. After completing the first five batches, 500 data samples were randomly selected for manual verification. The agents’ prompts were continuously optimized based on feedback, effectively mitigating LLM hallucination phenomena [39] and ensuring that the automated workflow maintained both high efficiency and high accuracy with classification consistency. By deconstructing the complex cultural perception task into four sequential stages—semantic qualification, geospatial alignment, fine-grained extraction, and logical self-review—the workflow effectively alleviates the information loss problem in long-text processing and, through the self-reflection mechanism, significantly enhances data processing accuracy.

To ensure high stability and reproducibility of spatial semantic extraction by the LLM under zero-shot conditions, this study designed specific Chain-of-Thought (CoT) constraints for each of the four agents. The complete prompt template design, input-output format restrictions, and the human-in-the-loop iterative calibration process ensuring output quality are detailed in Appendix A. The Self-Correction and Reflection Agent is triggered by explicit thresholds: (1) confidence score < 0.70; (2) contradictory entity–aspect pairs; (3) ABSA output inconsistency flagged by cross-validation; or (4) spatial entity outside

Beijing or not in gazetteer. Once triggered, it executes five consistency checks (carrier–culture alignment, sentiment–aspect–carrier coherence, spatial uniqueness, cultural-type mutual exclusivity, and carrier–typology consistency) and invokes re-reasoning for detected inconsistencies. The complete rule sets, examples, and prompt template are detailed in Appendix A.4.

2.2.2. Local Deployment of Large Language Models

Current large language models represented by GPT, Gemini, and Qwen have introduced a new paradigm for natural language processing tasks. Their multiple versions demonstrate exceptional capabilities in text understanding and generation, enabling the execution of specialized tasks with only a small number of examples without the need for costly fine-tuning [40]. Although foreign LLMs possess certain advantages in overall performance, domestic open-source LLMs also exhibit significant strengths in Chinese language processing [41]. To avoid the costs and privacy risks associated with repeated invocation of commercial APIs, and based on model evaluation results, this study comprehensively adopted the locally deployed open-source model Qwen3-32B as the primary experimental model and rented a compatible high-performance computing server to ensure stable model operation. Simultaneously, results were verified using the domestically advanced open-source DeepSeek-V3 model. Existing research has demonstrated that this model not only performs notably in complex interactive scenarios but also exhibits significant advantages in text style adjustment, expression refinement, and domain-specific text processing [42], while demonstrating strong stability in social science research text processing [43], making it highly compatible with the practical application requirements of this study.

2.2.3. TF-IDF-Based Text Semantic Analysis

The TF-IDF (Term Frequency-Inverse Document Frequency) algorithm is a commonly used weighting technique in text classification for evaluating the importance of terms to documents: if a term appears frequently in a specific document but infrequently across the overall document collection, it is considered to have strong categorical discrimination capability [44]. This study used the Jieba tool to perform Chinese word segmentation on the Weibo texts, sequentially converting text content into ordered word sequences. Subsequently, the TF-IDF algorithm was applied to conduct text information mining on the social media data, performing word frequency statistics on all Weibo texts to support the agents' feature extraction and subsequent spatial analysis.

2.2.4. Sentiment Score Calculation

The sentiment polarity of each text has already been determined by the ABSA Agent described in Section 2.2.1. To enable subsequent entropy-weighted aggregation and spatial analysis, this step numerically transforms the LLM-generated polarity labels via a deterministic mapping: positive, neutral, and negative are assigned base scores of +1, 0, and −1, respectively [45,46].

Building on this, in conjunction with the 17 specific evaluation aspects (Table A1) and based on the sentiment performance differences across these aspects, the entropy weight method was employed to determine the objective weights of each indicator. Specifically, the average sentiment score of each evaluation aspect served as the indicator input; its information entropy was calculated and used to determine the weights, thereby reflecting the relative importance of different evaluation dimensions in overall sentiment expression.

A multi-dimensional sentiment weighting model was further constructed to perform weighted calculation of individual text sentiment, expressed as:

$$S = \sum_{i=1}^{17} w_i s_i \quad (1)$$

where S represents the composite sentiment score, w_i is the weight of the i -th evaluation aspect, and s_i is the base sentiment score corresponding to that dimension. The specific numerical distributions of information entropy, differentiation coefficients, and final objective weights for each aspect, calculated based on the full set of valid perception data, are detailed in Appendix B (Table A2).

In terms of spatial analysis, sentiment scores were spatially matched with the texts' geographic coordinates. The kernel density estimation (KDE) method was employed to characterize the spatial distribution intensity and clustering characteristics of sentiment. Building on this, the Min-Max normalization method was applied to standardize the KDE results across different cultural types and evaluation dimensions, eliminating dimensional differences and enabling horizontal comparison across different dimensions and cultural types, thus providing quantitative support for the analysis of spatial differentiation characteristics of capital cultural sentiment.

2.2.5. Tensor Decomposition

Tensor decomposition represents a class of multi-dimensional extension methods for higher-order data structure analysis. Its core principle is to express a high-dimensional tensor as a combination of several low-rank factor matrices, thereby revealing potential higher-order association structures among variables. To characterize the complex interaction relationships among multi-dimensional semantic elements in cultural perception, this study constructed a four-mode tensor. Compared to two-dimensional or three-dimensional statistical methods, tensor decomposition can simultaneously model the higher-order coupling relationships among cultural types, evaluation aspects, sentiment polarity, and spatial carriers, avoiding information loss during dimensionality reduction and thus revealing more complex latent semantic structures. The four-mode tensor corresponds to four dimensions: cultural type (4 categories), evaluation aspect (17 categories), sentiment polarity (3 categories), and spatial carrier (5 categories). The original tensor is expressed as:

$$x \in R^{I \times J \times K \times L} \quad (2)$$

where $I = 4$, $J = 17$, $K = 3$, and $L = 5$. Each tensor element represents the composite perception intensity under conditions of the i -th cultural type, j -th evaluation aspect, k -th sentiment polarity, and l -th spatial carrier category.

This study employed CP decomposition to achieve higher-order tensor decomposition, initialized with 50 random non-negative initializations and selecting the one with minimum reconstruction error. The maximum iteration count was set to 500 with a convergence threshold of 1×10^{-6} . To ensure reproducibility, the random seed was set to 42. The original tensor was subjected to low-rank approximation, expressed as a linear superposition of R rank-one tensors:

$$x \approx \sum_{r=1}^R \lambda_r a_r \circ b_r \circ c_r \circ d_r \quad (3)$$

where λ_r represents the weight of the r -th latent pattern; $a_r \in R^I$, $b_r \in R^J$, $c_r \in R^K$, and $d_r \in R^L$ are the factor vectors respectively corresponding to cultural type, evaluation aspect, sentiment polarity, and spatial carrier type dimensions; and the symbol $\circ$ denotes the vector outer product operation.

Each decomposed rank-one component can be interpreted as a latent ‘cultural perception pattern,’ reflecting the sentiment expression structure of users on certain evaluation dimensions within a specific cultural context. To prevent any single factor weight from dominating the interpretation process, this study applied a fourth-root scaling to the weight λ of each pattern and evenly distributed it across all dimensional factors, thereby enhancing cross-dimensional interpretation consistency. To enhance model interpretability, non-negativity constraints were imposed on all factor matrices:

$$a_r, b_r, c_r, d_r \geq 0 \quad (4)$$

thus ensuring that all dimensional weights possess clear physical meaning. The semantic interpretation of each latent pattern is based on the maximum weight principle across dimensions, i.e., selecting the cultural type, evaluation aspect, and carrier with the highest contribution as the dominant semantics of that pattern. Rank selection was evaluated using the Elbow Method, determining that at $R = 9$, the model explains nearly 95% of variance with error dropping below approximately 0.05, achieving optimal model robustness while maximally preserving the structural information of capital cultural perception. Therefore, this study selected rank $R = 9$ for subsequent analysis.

To ensure the reproducibility of the high-dimensional coupling model, the hyper-parameter configuration for non-negative CP decomposition is detailed in Appendix B (Table A3). Additionally, the methodological comparison and dimensional fidelity advantage analysis of selecting CP decomposition over traditional LDA or NMF models for multi-dimensional modeling are provided in Appendix B (Table A4).

3. Results

3.1. Analysis of Capital Cultural Perception Results

3.1.1. Statistical Analysis of Data Processing Results

During preprocessing, approximately 11.76 million records were cleaned to remove irrelevant content, retaining approximately 10.41 million valid texts as the full corpus. An agent semantic knowledge base was then constructed based on the four cultural type definitions (Table 1). The Cultural Classification Agent performed pairwise discrimination, filtering out irrelevant data. The ABSA Agent extracted ‘evaluation content–evaluation aspect–sentiment polarity’ triples, while the Spatial Entity Extraction Agent identified material cultural carriers and aligned them with POI database entries. After iterative refinement through the Self-Correction and Reflection Agent, approximately 277,000 valid records—constituting the geo-tagged analytical sample—were retained for spatial analysis.

To examine the reliability of the agentic workflow, we implemented multi-level performance verification. First, 500 texts were randomly selected for manual blind review, confirming that classification accuracy exceeded 95% for all four cultural types (Table 1). Second, cross-model consistency verification using DeepSeek-V3 as an independent evaluator on 2000 randomly sampled texts achieved an 86.20% agreement rate on joint ‘evaluation aspect–sentiment polarity’ prediction (with high-confidence human review agreement reaching 89.30%), demonstrating robust cross-model stability. Third, landmark evaluation aspect verification compared the top-three aspects extracted by Qwen3-32B for Beijing’s Top-20 landmarks against expert-established ground truth, yielding an average semantic overlap rate of 76.90%, further corroborating the effectiveness of the agentic workflow. To validate the workflow against a supervised baseline, we fine-tuned BERT-base-Chinese (110 M parameters) and compared it with Qwen3-32B zero-shot inference. BERT achieved Macro-F1 = 0.5723 and Accuracy = 0.6837, while Qwen3 achieved Macro-F1 = 0.5919 and Accuracy = 0.6757. McNemar’s paired test ($\chi^2 = 2.96$, $p = 0.085$; Cohen’s $h = 0.0173$) indicated

no statistically significant difference, confirming that the zero-shot LLM approach achieves statistically equivalent performance to fine-tuned BERT without costly domain-specific fine-tuning.

Table 1. Frequency statistics and accuracy verification of capital cultural classification.

Cultural Type	Core Definition	Total Frequency	Proportion (%)	Accuracy	Precision	Recall	F1 Score
Ancient Capital Culture	As the national capital and a renowned historical and cultural city, Beijing boasts culturally precious heritage accumulated over a long period, standing as a remarkable testimony to the time-honored Chinese civilization.	148,403	53.60	0.918	0.869	0.809	0.838
Beijing-Flavor Culture	The customs and humanistic spirits nurtured by Beijing residents in long-term production and daily life embody local nostalgia and regional characteristics.	79,076	28.56	0.960	0.973	0.802	0.880
Red Culture	The culture forged by the Chinese people under the leadership of the Communist Party of China during revolution, construction and reform embodies the original aspiration and mission of Communists.	34,283	12.38	0.960	0.913	0.895	0.904
Innovative Culture	The culture cultivated amid the integrated development of technology, industry and culture in the new era represents the vivid practice of advanced socialist culture in the capital.	15,099	5.45	0.972	0.844	0.970	0.903

Collectively, these multi-level verification results—manual blind review, cross-model consistency, landmark validation, and supervised baseline comparison—provide converging evidence that the LLM-driven agentic workflow reliably extracts fine-grained cultural perception at scale.

From the perspective of cultural type frequency distribution, capital cultural perception exhibits a highly unbalanced hierarchical structure: Ancient Capital Culture, with a total frequency of 148,403 and a share of 53.60%, occupies an absolutely dominant position, constituting the core vehicle of public cognition of capital culture and demonstrating that historical heritage and cultural roots serve as the primary entry point for public perception of capital culture. Beijing-Flavor Culture, with a frequency of 79,076 and a share of 28.56%, forms the second tier, reflecting the important supporting role of lifestyle-oriented, localized neighborhood scenes in public cultural perception. In contrast, Red Culture (34,283 occurrences, 12.38%) and Innovative Culture (15,099 occurrences, 5.45%) account for significantly lower proportions, together comprising less than 18%. This indicates that the exposure and attention received by contemporary Innovative Culture and Red Culture in public perception are far weaker than those of historical and lifestyle-oriented cultures, presenting a perceptual structural imbalance characterized by ‘thick history, heavy lifestyle, light innovation, weak red.’

To examine the reliability of the LLM agentic workflow in text parsing, this study implemented multi-level performance verification. First, for the cultural type classification task, 500 Weibo texts were randomly selected for manual blind review verification. The results indicated that the classification accuracy for all four cultural types exceeded 95% (Table 1). Subsequently, to further evaluate the generalization performance of high-dimensional long-tail ABSA and spatial entity extraction, this study introduced two benchmark auxiliary verifications. (1) Cross-model consistency verification: The DeepSeek-V3 LLM was employed as an independent evaluator to conduct blind cross-examination of the primary model's (Qwen3-32B) prediction results. Among 2000 randomly sampled texts, the agreement rate between the two models on joint 'evaluation aspect-sentiment polarity' prediction reached 86.20% (with the high-confidence-interval human review agreement rate reaching 89.30%), indicating that the agentic workflow possesses highly stable cross-model robustness in parsing complex Chinese cultural semantics. Detailed fine-grained verification metrics are provided in Appendix B (Table A5). (2) Landmark evaluation aspect verification: Using the standard attribute characteristics (Ground Truth) of Beijing's Top-20 renowned landmarks constructed by domain experts as the benchmark, the top-three (Top-3) core evaluation aspects automatically identified and extracted by Qwen3-32B for each landmark were compared. The results showed an average semantic overlap rate of 76.90% between the model output and the expert benchmark. The high concordance at the micro-level further corroborated the effectiveness and scientific validity of the agentic workflow in spatial carrier binding and cultural perception dimension parsing.

3.1.2. Cross-Analysis of Cultural Types and Evaluation Aspects

This study first employed the LLM for evaluation aspect classification and, with reference to existing literature, formulated operational definitions for each evaluation aspect, ultimately identifying four major categories comprising 17 sub-categories as the primary evaluation aspects of this study (Table 2). And the operational definitions, typical trigger words, and literature support basis in geography and social sensing domains for these 17 evaluation aspects are detailed in Appendix B (Table A1).

Table 2. Capital cultural evaluation aspects.

Evaluation Dimension	Evaluation Aspects and Supporting Literature
Cultural Value and Inheritance	Cultural experience [47–50], cultural atmosphere [51–53], cultural connotation [54–57], architectural aesthetics [58–60], historical cognition [61–63], cultural heritage [64–66]
Service Facilities and Convenience	Catering experience [67–69], business environment [70–72], public facilities [73,74], transportation convenience [75,76], tourist services [77,78]
Experience Quality and Comfort Level	Visitor flow [78–80], physical Exertion [81], emotional resonance [82–84], weather and climate [85,86]
Natural Landscape and Environment	Natural landscape [57,85], cultural landscape [56,62]

To further compare the specific proportions of the 17 evaluation aspects corresponding to each cultural type, this study conducted cross-comparison using cultural type and evaluation aspect as dimensions, analyzing the fine-grained evaluation distribution of each culture type and the cultural type attribution of each aspect. The cross-comparison results are illustrated in Figure 2. Statistical verification of the classification results was performed using the Chi-square test, yielding a significance level of $p < 0.001$, indicating the existence of extremely significant statistical associations between different cultural types

and audience perception evaluation dimensions, thereby confirming the rigorous logical validity of the classification system.

Dual Dimension Analysis of Capital Culture Perception

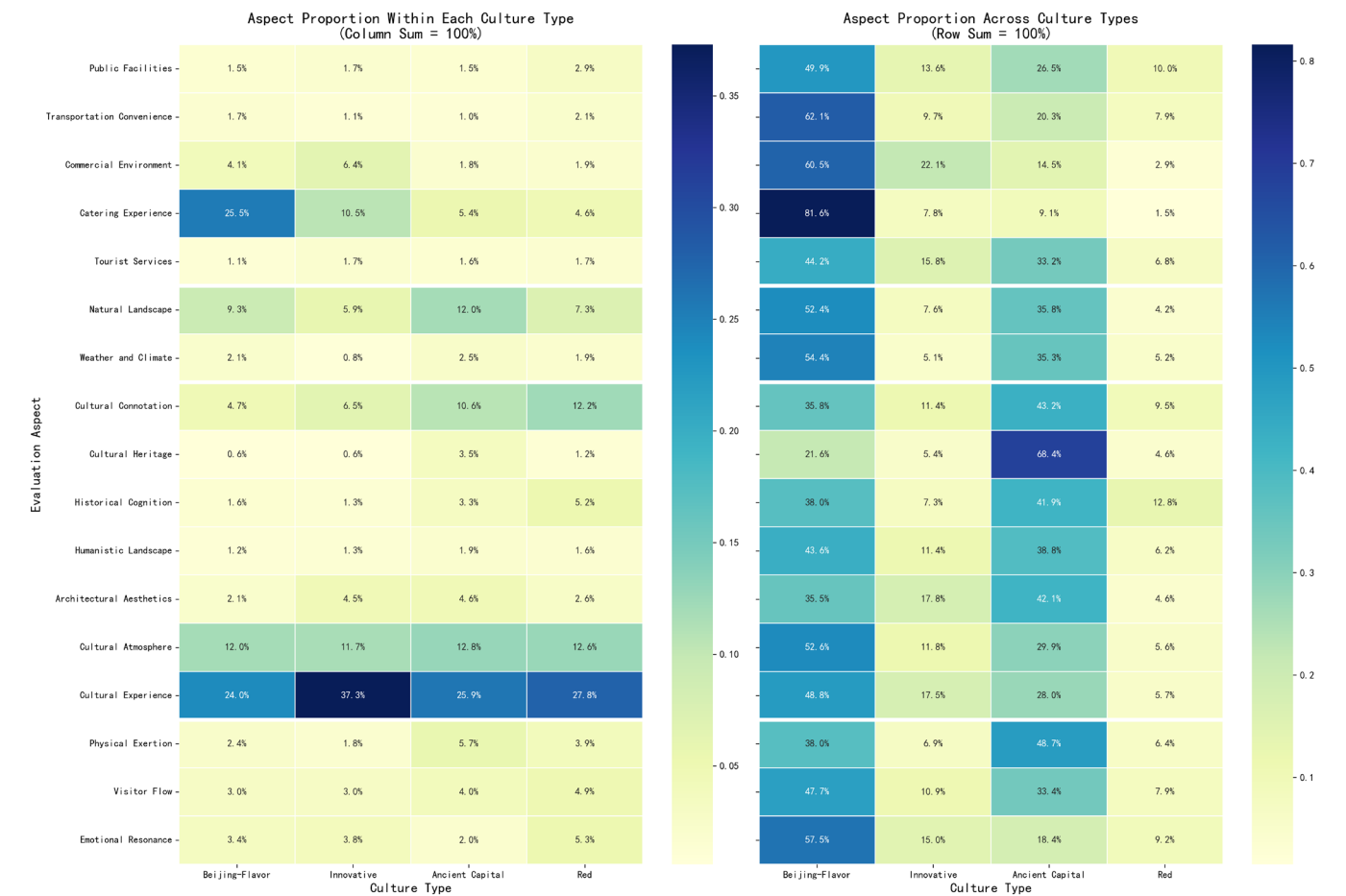


Figure 2. Cross-analysis of cultural types and evaluation aspects.

From the cultural perception perspective, the four types of capital culture have formed differentiated perception centers and cognitive frameworks (left half of Figure 2). Beijing-Flavor Culture is centered on lifestyle-oriented experiential perception, with culinary experience (25.5%) and cultural experience (24.0%) together accounting for nearly half, with public perception highly anchored to concrete scenes such as neighborhood life and local culture, presenting a perception logic of ‘life as culture.’ Innovative Culture is centered on interactive, participatory perception, with cultural experience reaching 37.3%, significantly higher than other types, supplemented by cultural atmosphere (11.7%) and commercial environment (6.4%), reflecting the perception characteristic of contemporary culture as ‘scenarized and participatory.’ Ancient Capital Culture is centered on heritage-viewing perception, with cultural heritage accounting for as much as 68.4%, supplemented by cultural atmosphere (12.8%) and natural landscape (12.0%), forming a perception structure of ‘static heritage + environmental atmosphere,’ with public cognition more inclined toward symbolic recognition of historical roots. Red Culture is characterized by perception that equally emphasizes connotation and experience, with cultural experience (27.8%), cultural connotation (12.2%), and cultural atmosphere (12.6%) being evenly distributed, coupled with a slightly higher share of public service elements, reflecting a perception

formation mechanism driven by the combined effects of ideological dissemination and scenographic support.

Combined with further standardized residual analysis, the perception boundaries, element exclusivity, and deep structural characteristics of each cultural type can be precisely revealed. Overall, capital cultural perception exhibits a macro-structure of ‘strong lifestyle-oriented and historical culture, weak spiritual and innovative culture.’ Beijing-Flavor Culture is rooted in citizens’ daily lives, with folk customs, time-honored brands, and life scenes as core carriers, forming the most extensive spontaneous cognitive coverage. Statistical results show that lifestyle services and daily consumption elements are heavily biased toward Beijing-Flavor Culture, with culinary experience accounting for 81.6% of Beijing-Flavor Culture, and its standardized residual reaching as high as 82.29, the highest among all cross-terms, exhibiting extremely significant positive deviation. This directly quantifies and confirms Beijing-Flavor Culture’s absolute perceptual positioning as a ‘lifestyle-oriented culture’ highly bound to daily travel, leisure, and consumption behaviors, possessing strong ‘label monopolization’ over public cognition in the culinary dimension. Conversely, Ancient Capital Culture, Red Culture, and Innovative Culture all exhibit extremely significant negative residuals in culinary experience, reflecting that the public automatically strips away daily consumption labels when perceiving these serious or modern cultural forms.

Ancient Capital Culture, centered on historical heritage, urban layout, and cultural lineage inheritance, relies on explicit historical symbols such as the Central Axis, the old city, and imperial gardens, possessing strong visual recognizability and symbolic authority, making it the second largest perception source after Beijing-Flavor Culture. Historical heritage elements are highly concentrated here: Ancient Capital Culture exhibits extremely strong positive significance in cultural heritage, cultural connotation, architectural aesthetics, and historical cognition, reflecting its symbolic perception advantage as the root of Chinese civilization. Notably, Ancient Capital Culture’s positive residual in the ‘physical exertion’ dimension is also extremely high (residual 36.10), suggesting that the grand spatial scale and depth of exploration of the old city and historical landmarks create a distinctive perception characteristic of ‘heritage touring coexisting with physical constraints.’ In contrast, Red Culture emphasizes spiritual connotation and value guidance, leaning toward the ideological and educational dimensions, with relatively limited frequency and intensity of spontaneous public contact and mention. Nevertheless, in specific spiritual dimensions, its perception boundaries are extremely clear: Red Culture exhibits highly positive deviations in historical cognition and cultural connotation, and its positive residual in ‘emotional resonance’ is as high as 14.92, directly quantifying and validating Red Culture’s unique spiritual appeal and ideological education function, demonstrating the distinctive cohesive power of spiritual culture. Innovative Culture, as an emerging cultural form, is still in the process of cultivating spatial carriers and experiential scenes, having not yet formed a nationwide, normalized perception foundation. However, as the core vehicle of contemporary capital cultural perception transformation, it exhibits distinct ‘scenarized, participatory’ characteristics, showing significant positive bias in cultural experience and commercial environment, strongly supporting the common development trend of propelling capital culture ‘from passive viewing to active participation.’

To further verify the rationality of multi-label classification, this study conducted evaluation aspect priority verification on the Top-20 renowned landmarks, analyzing the top-three evaluation aspects corresponding to each landmark. The results indicate that the evaluation aspect priorities of renowned landmarks exhibit high cultural type consistency: For the Forbidden City (N = 127), the top-three evaluation aspects are cultural experience, natural landscape, and cultural atmosphere, corroborating its comprehensive

perception attributes as an Ancient Capital Culture landmark. For the Great Wall ($N = 43$), physical exertion jumps to the second evaluation aspect, forming a perfect micro-level echo with the significant positive residual of Ancient Capital Culture in ‘physical exertion’ (36.10) identified in the preceding macro-level statistics, revealing the distinctive perception structure of heritage touring coexisting with physical constraints. For Nanluoguxiang ($N = 44$), commercial environment becomes the top evaluation aspect (surpassing cultural atmosphere), directly quantifying the displacement effect of commercialization intervention on the perception center of traditional neighborhoods. For Tiananmen Square ($N = 15$), visitor flow becomes the second aspect, further corroborating the spatial centrality and high-density usage characteristics of core Red Culture venues, complementing its significant positive deviation in public facilities (residual 12.79). The high consistency between the above landmark-level verification results and the overall perception patterns further supports the internal consistency and scientific rigor of this study’s classification system and analytical framework.

3.1.3. Spatial Distribution Characteristics of Capital Cultural Perception

To further reveal the spatial perception patterns of the four cultural types, this study employed kernel density estimation (KDE) and Getis-Ord G_i^* hotspot analysis methods to analyze the spatial distribution characteristics of approximately 277,000 valid data records. Getis-Ord G_i^* displays only cold spots and hot spots with a 99% confidence level. The spatial perception characteristics of the four cultural types are described below.

The spatial perception results of Beijing-Flavor Culture exhibit a distinct ‘monocentric agglomeration with multi-directional dispersion’ pattern. KDE analysis (Figure 3) shows that the perception center of gravity is tightly anchored in the old city core area within the Second Ring Road, forming contiguous high-value zones centered on Shichahai, Dashilar, and Nanluoguxiang, reflecting the spatial stability of traditional historical neighborhoods as the birthplace of Beijing-Flavor Culture. Combined with word frequency statistical results, this spatial distribution is highly congruent with perception carriers. The perception carriers are rooted in residential spaces such as ‘hutong’ and ‘siheyuan’ (courtyard houses), extending toward lifestyle consumption symbols such as ‘Peking duck,’ ‘zhajiangmian’ (noodles with fried sauce), and ‘Deyunshe’ (cross-talk society). These symbols with strong secular lifestyle attributes and ‘locality’ enable Beijing-Flavor Culture’s perception scope to transcend the physical boundaries of static historical relics, diffusing along with modern commercial forms into contemporary urban public spaces such as Wangfujing and Shichahai.

The spatial perception of Ancient Capital Culture exhibits extremely strong ‘mononuclear agglomeration with axial extension’ characteristics, reflecting the absolute dominant position of Beijing’s material civilization substrate as a millennia-old capital in citizens’ cognition. KDE results show that the high-value perception center of Ancient Capital Culture is tightly anchored in the old city’s historical core area centered on the Forbidden City and Jingshan Park, exhibiting extremely high spatial centrality. This highly agglomerated spatial pattern is mutually corroborated by high-frequency carrier characteristics. The perception carriers of Ancient Capital Culture are centered on iconic historical heritage symbols such as the Forbidden City, Tiananmen, the Great Wall, and the Temple of Heaven, constituting the ‘material substrate’ of perception. These high-frequency entities represent not only high-level world heritage but also the concrete expression of the ancient capital’s spiritual core. Meanwhile, the perception pathway exhibits a trend of permeation from ‘grand narrative’ toward ‘everyday space’—the high-frequency appearance of ‘hutong,’ ‘Nanluoguxiang,’ and specific historical place names in word frequency indicates that Ancient Capital Culture has spatially transcended enclosed museum-style display, deeply

coupling with citizens' residential neighborhoods, forming a perception continuum of 'heritage landscape–living history.'

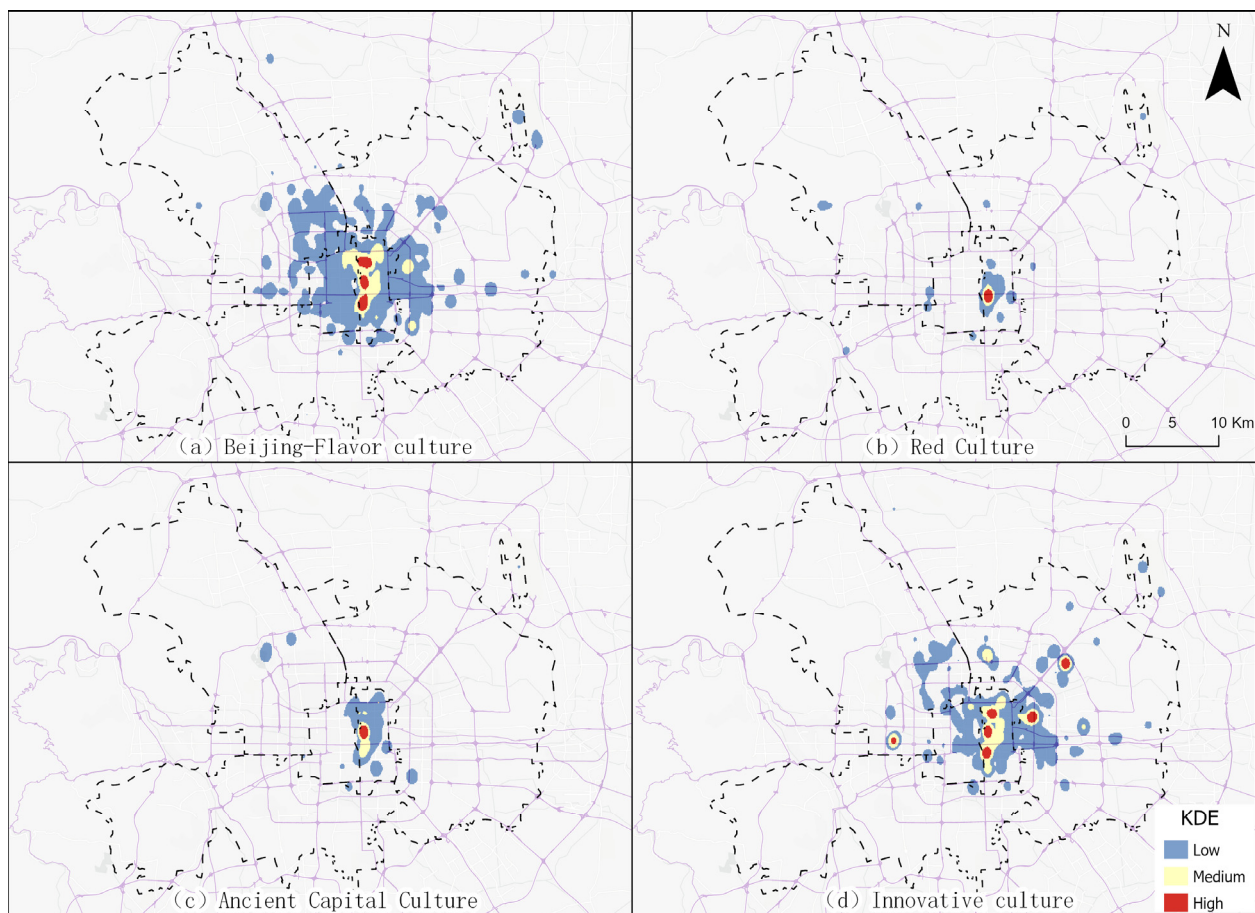


Figure 3. Spatial kernel density analysis of perception of capital culture.

The spatial perception of Red Culture exhibits extremely strong 'spatial anchoring' and 'political centrality,' being the type with the clearest geographic boundaries and most concentrated perception intensity among Beijing's four cultural types. KDE shows that the high-value perception zone of Red Culture presents an absolute mononuclear agglomeration pattern, with its core tightly anchored in a narrow strip centered on Tiananmen Square and radiating east–west along Chang'an Avenue. This spatial pattern is fully congruent with the entities extracted through word frequency statistics: the perception core is constituted by national-level political symbolic architecture such as Tiananmen, the Monument to the People's Heroes, and the National Museum. These carriers are not merely physical entities but meaning anchors that carry national memory and political ritual. The co-occurrence of high-frequency temporal terms (e.g., 'flag-raising ceremony,' 'anniversary,' 'National Day') with spatial entities reveals the deep integration of temporality and spatiality in Red Culture perception—the public transforms grand national narratives into embodied emotional identification by participating in ritual activities within specific sacred spaces.

The spatial perception of Innovative Culture exhibits significant 'polycentric extension' and 'asymmetric deviation' characteristics, reflecting Beijing's spatial functional transformation in the context of constructing an International Science and Technology Innovation Center. KDE shows that the perception center of gravity of Innovative Culture breaks away from the traditional centripetal distribution, exhibiting a significant 'northward deviation' trend. High-value zones are primarily concentrated in the Haidian area in the northwest (centered on Zhongguancun) and the Chaoyang area in the northeast (centered on the

798 Art District and Wangjing). Combined with word frequency characteristics, the perception core of Innovative Culture is constituted by cultural carriers such as art galleries, the National Centre for the Performing Arts, and contemporary art, as well as specific landmarks such as Zhongguancun and Sanlitun. High-frequency terms such as ‘digital,’ ‘fashion,’ and ‘cross-boundary’ indicate that citizens’ cognition of Innovative Culture has transcended the singular technological domain, transforming into a cross-boundary aesthetic experience encompassing art, design, and urban life. This carrier characteristic is directly mapped onto space, manifesting as the dual agglomeration of perception hotspots in science-education innovation zones and international cultural creative zones.

Hotspot analysis further supplements and verifies the above KDE-based spatial characteristics across four cultural types (Figure 4). In terms of Beijing-Flavor Culture (a), hotspot results identify contiguous significant clustering within the old city core; nevertheless, non-significant areas or ‘cold spots’ of perception emerge in core macro-political heritage areas such as the Forbidden City. This reflects that within the capital’s core space, significant spatial functional displacement exists between the neighborhood-style ‘Beijing-Flavor narrative’ and the grand ‘Ancient Capital narrative,’ exhibiting a distribution trend of ‘encircling the core, permeating toward the everyday.’

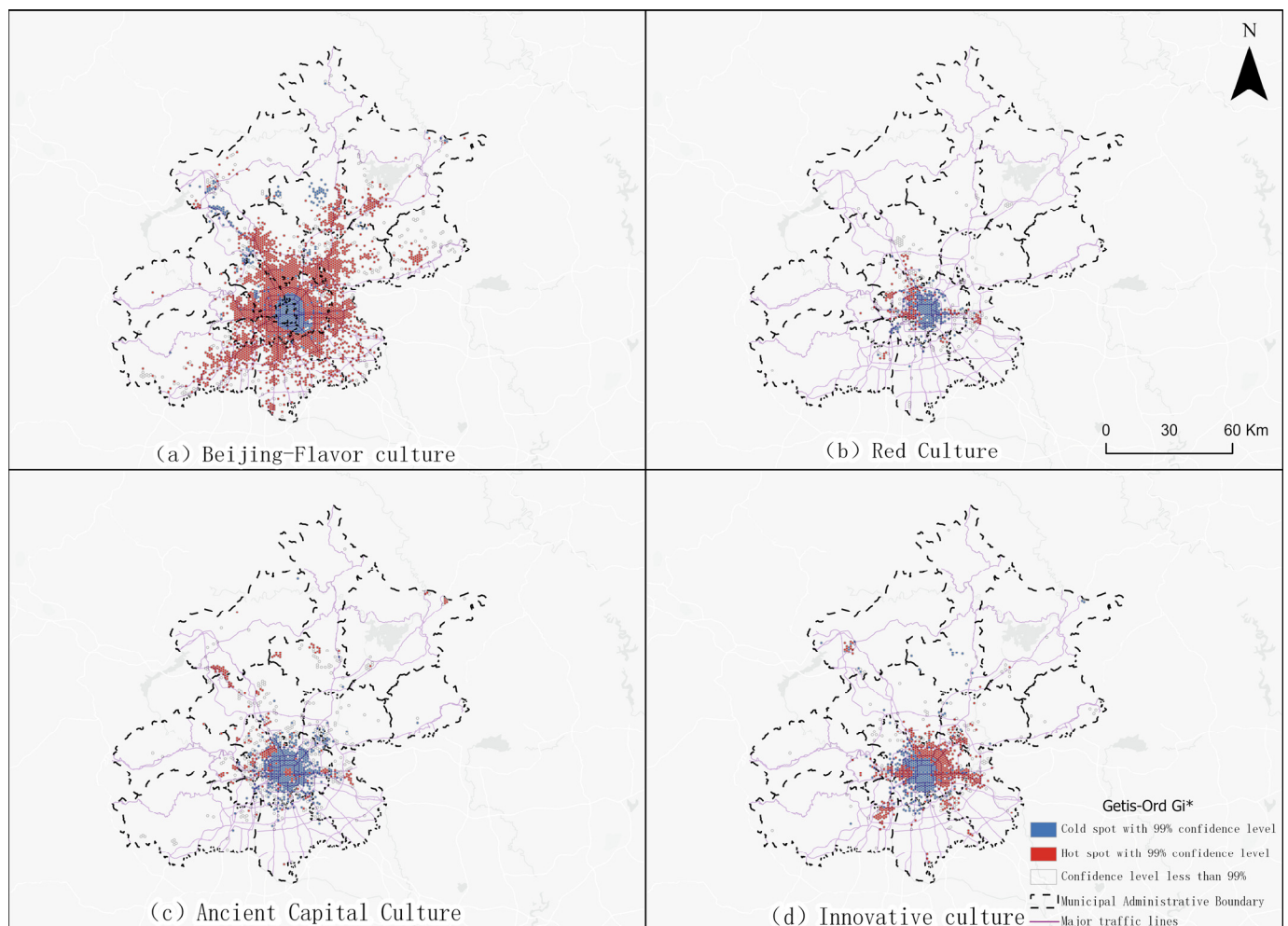


Figure 4. Hotspot analysis of perception with respect to capital culture.

For Ancient Capital Culture (c), hotspot analysis further confirms that the Forbidden City-centered historical core forms a contiguous significant hotspot, revealing that Ancient Capital Culture perception possesses profound spatial path dependence—that is, the

intensity of cultural cognition and the richness of historical material relics are highly spatially congruent. Beyond the core urban hotspot zone, scattered significant hotspots formed along the northern mountainous area (along the Great Wall) reflect the point-axis extension characteristics of Ancient Capital Culture perception in space, pushing the perception boundary from the inner city toward broader regional landscapes.

With regard to Red Culture (b), hotspot analysis further validates its unique spatial attributes: the high-confidence significant hotspot area is relatively small in extent and structurally compact, exhibiting extremely strong spatial centripetal force. Unlike the diffusivity of Beijing-Flavor Culture, Red Culture's perception hotspots exhibit steep distance decay characteristics with increasing geographic distance. This spatial gradient reflects that Red Culture carriers possess significant genius loci and sacredness, with their perception logic highly dependent on the physical presence of core political landmarks.

As for Innovative Culture (d), hotspot analysis confirms that its significant hotspots present a multi-point scattered distribution, which is highly congruent with the city's modern functional zoning. This uneven spatial distribution pattern reveals Innovative Culture perception's strong dependency on high-tech industry clusters and contemporary art fields across urban functional districts.

Comprehensive analysis indicates that Beijing's capital cultural perception spatially presents an unbalanced pattern of 'high coupling in the core area with differentiated expansion at the periphery.' In geographical representation, Ancient Capital Culture and Red Culture exhibit extremely strong 'spatial anchoring force,' respectively relying on imperial heritage and the national political-spiritual origin to form highly centripetal agglomeration cores with clear boundaries. Beijing-Flavor Culture and Innovative Culture exhibit stronger 'spatial permeability': the former flows into everyday crevices through geo-lifestyle, while the latter undergoes spatial deviation following the city's modern functional zoning, driving the reproduction of cultural resources in geographic space. This pattern profoundly reflects that public perception has completed a cognitive reconstruction from 'abstract symbolic mapping' to 'embodied scenographic experience,' enabling capital culture to achieve the dialectical unity of historical depth, political core, geo-folk custom, and contemporary vitality in the spatial dimension.

3.2. Analysis of Capital Cultural Evaluation Results

3.2.1. Multi-Dimensional Perception and Spatial Differentiation Characteristics

This study integrated the 17 fine-grained evaluation aspects extracted by the LLM into four major evaluation dimensions: 'Cultural Value and Heritage,' 'Natural Landscape and Environment,' 'Service Facilities and Convenience,' and 'Experience Quality and Comfort.' Material cultural carriers were clustered into five main spatial categories: imperial historical-cultural heritage, traditional residential and historical districts, modern commercial and urban leisure culture, public cultural display and performance, and political symbols and Red Culture. Statistical verification of the above classification results was performed using the Chi-square test: under conditions of $\chi^2 = 46,409.39$ and $df = 64$, the significance level $p < 0.001$, indicating the existence of highly non-random associations among material carriers, evaluation dimensions, and sentiment polarity, confirming the rigorous logical validity of the classification system. This study established a value transmission chain through a Sankey diagram (Figure 5), mapping the spatial pattern of cultural types onto the analysis of evaluation dimensions, thereby revealing the spatial differentiation characteristics of perceived value across dimensions and presenting the transmission pathways of perception flow in a panoramic manner.

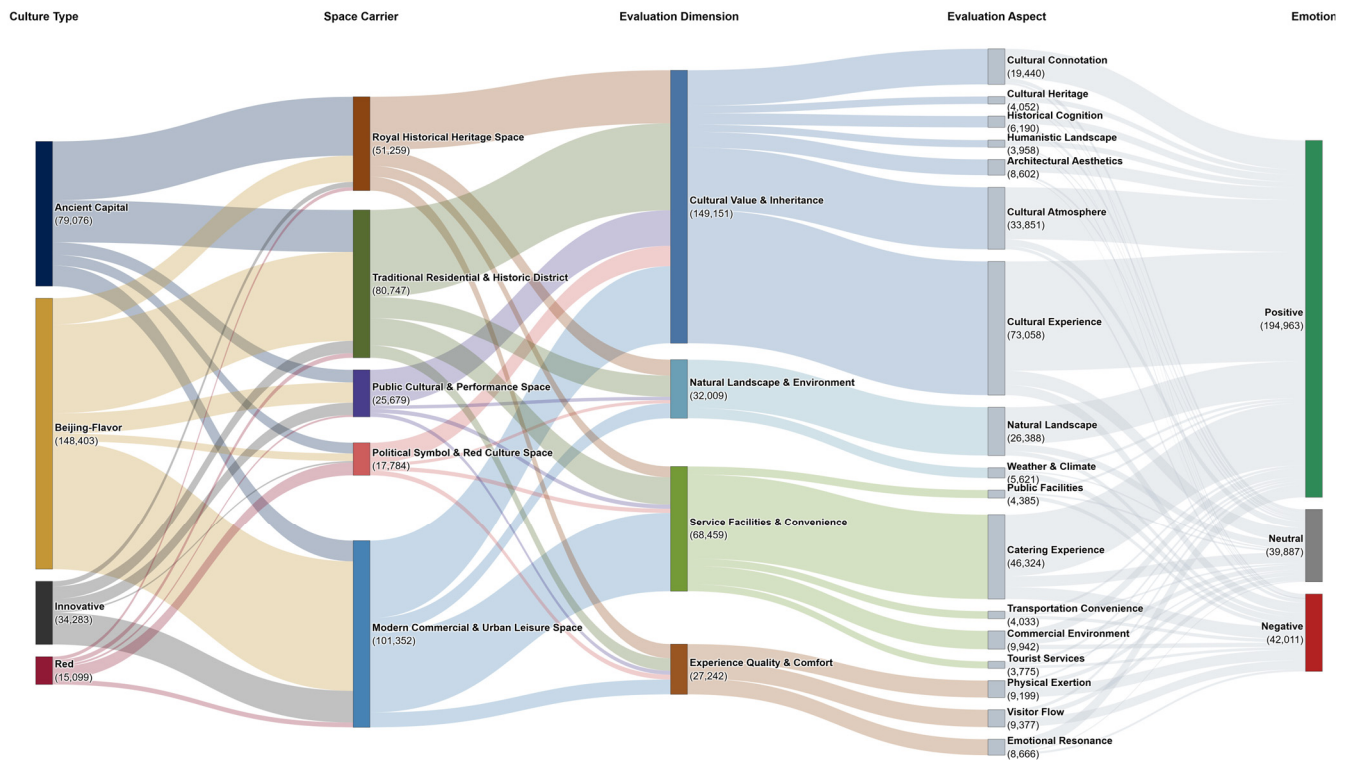


Figure 5. Five-dimensional perception Sankey diagram.

The five-layer Sankey diagram clearly reveals the topological transmission network of capital cultural perception from macro-level types to micro-level sentiment transformation (Figure 5). From the perspective of transmission pathways, cultural types first achieve spatial positioning through specific ‘material carriers,’ subsequently stimulating evaluations across different dimensions. Specifically, Beijing-Flavor Culture has the largest volume, with its perception flow primarily channeled into modern commercial and urban leisure spaces and traditional residential neighborhoods, ultimately converging into service facilities and experience quality dimensions. Ancient Capital Culture heavily depends on imperial historical-cultural heritage spaces, serving as the absolute core driving perception in cultural value and natural landscape dimensions. Innovative Culture primarily relies on public cultural display and performance spaces, flowing toward experience quality and service facilities. Red Culture, compact in volume, precisely anchors onto political symbol and Red Culture spaces, with emotional resonance as its core touchpoint.

Each evaluation dimension is further decomposed into specific evaluation aspects: the Cultural Value and Heritage dimension is centered on cultural experience and cultural atmosphere; the Natural Landscape and Environment dimension is dominated by natural landscape; the Service Facilities and Convenience dimension takes culinary experience and commercial environment as core implementation scenarios; the Experience Quality and Comfort dimension encompasses three balanced touchpoints: emotional resonance, visitor flow, and physical exertion. Ultimately, the perception of each evaluation aspect transforms into three sentiment attitudes—positive, neutral, and negative: the cultural value and natural landscape experiences dominated by Ancient Capital Culture and Beijing-Flavor Culture serve as the core sources of positive sentiment; the service facility experiences driven by Innovative Culture mostly elicit neutral evaluations, reflecting a state of ‘functionally basically adequate but experience falling short of expectations’; visitor flow and physical exertion issues within the experience quality dimension are the primary triggers of negative sentiment; Red Culture, though limited in volume, forms a unique positive sen-

timent supplement at the emotional resonance level. Together these constitute a complete logical closed loop from value sources to public sentiment feedback in capital culture.

(1) Cultural Value and Heritage Dimension: This dimension exhibits the highest perception intensity, dominated by cultural experience and atmosphere. The perception flow is primarily driven by Ancient Capital Culture and imperial heritage carriers, with positive sentiment high-value zones precisely anchored to core heritage sites such as the Forbidden City, Tiananmen, and the Temple of Heaven, exhibiting clear concentric diffusion and gradient attenuation toward surrounding historical neighborhoods with increasing geographic distance. This profoundly reveals the powerful driving and spatial commanding effect of high-energy-level cultural resource spatial density on public value identification.

(2) Natural Landscape and Environment Dimension: This dimension centers on natural landscape evaluation. Data flow indicates that natural landscape perception exhibits a strong coupling relationship with the imperial garden carriers of Ancient Capital Culture. In spatial positioning, perception hotspots are not only concentrated in historical famous gardens such as the Summer Palace and Yuanmingyuan but also extend toward the northern mountainous Great Wall belt, the Olympic Park, and urban green buffer zones on the city's periphery. This indicates that Beijing's 'mountain-water city' historical spatial framework still plays a deep foundational role in contemporary public natural aesthetic cognition.

(3) Service Facilities and Convenience Dimension: This dimension takes culinary experience and commercial environment as core scenarios, with the tightest binding to Beijing-Flavor Culture and modern leisure spaces. Wangfujing, Nanluoguxiang, and Sanlitun constitute perception hotspots. Notably, significant perception differentiation exists within this space: culinary experience contributes a large volume of positive evaluations, while 'commercial environment' triggers dense negative feedback. This spatial overlap intuitively reveals the perception tension between commercial logic expansion and cultural authenticity preservation during the revitalization transformation of historical neighborhoods.

(4) Experience Quality and Comfort Dimension: This dimension exhibits pronounced sentiment divergence at the perception endpoint. On one hand, negative perception points triggered by 'visitor flow' and 'physical exertion' are highly congruent with high-traffic tourism nodes such as the Forbidden City and Badaling, revealing the hard constraint on experience quality from core spatial carrying capacity oversaturation. On the other hand, the 'emotional resonance' element forms highly concentrated positive sentiment hotspots within Red Culture spaces. This spatial perception polarization triggered by different carriers within the same dimension proves that spatial attributes (tourism attributes vs. political commemorative attributes) exert a decisive reshaping effect on the public's ultimate experience quality.

3.2.2. Spatial Distribution of Composite Sentiment Scores

For each Weibo text, this study employed the entropy weight method to comprehensively weight and calculate sentiment scores in conjunction with the 17 evaluation aspects, calculating the average scores of the 17 evaluation aspects for each cultural type and visualizing them through rose diagrams (Figure 6).

From the overall pattern of spatial perception, public sentiment evaluation exhibits a significant 'cultural core-oriented' structure, indicating that 'Cultural Value and Heritage' constitutes the core concern of the majority of the public. Among the more fine-grained 17 evaluation dimensions (Figure 6), deep-level elements characterizing genius loci—such as 'cultural connotation,' 'cultural heritage,' and 'cultural experience'—constitute the core high-value agglomeration zone of sentiment. This indicates that in the human-place interaction process of cultural tourism, public perception of space is not uniformly distributed but highly focused on the ontological value of place. Deep cultural immersion consistently

serves as the primary mechanism for constructing a positive Sense of Place, with its sentiment weight significantly surpassing the basic attributes of material space, validating the core driving role of cultural capital in the emotional production of tourist destinations.

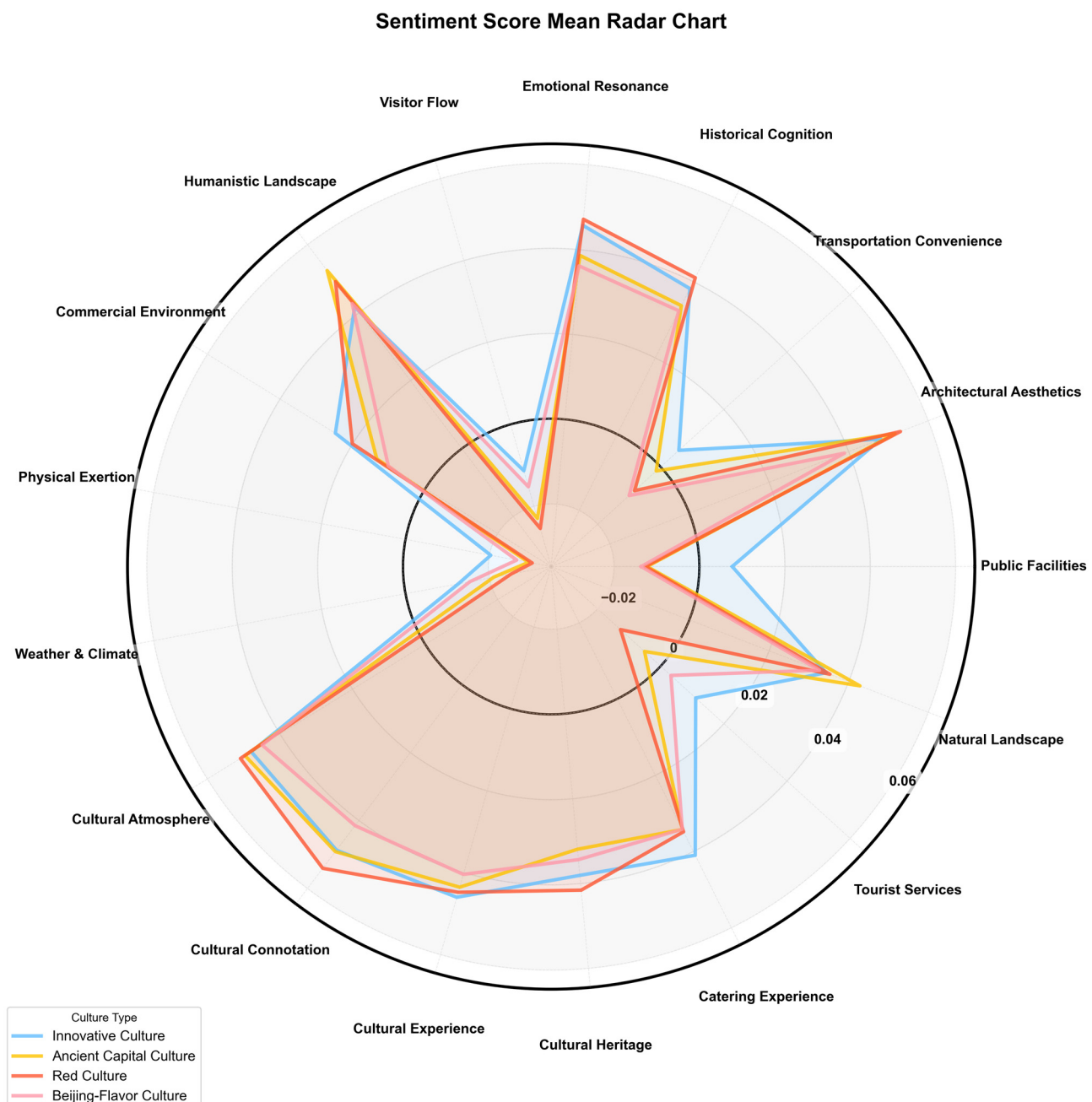


Figure 6. Rose diagram of average sentiment scores for 17 evaluation aspects.

Regarding the spatial differentiation characteristics of different cultural types, the data reveal pronounced type clustering and functional differentiation phenomena. ‘Red Culture’ and ‘Beijing-Flavor Culture’ exhibit high spatial isomorphism at the emotional level, with their high coupling in the dimensions of ‘architectural aesthetics,’ ‘historical cognition,’ and ‘humanistic landscape’ reflecting that these two types of cultural landscapes share a similar ‘historical-material’ narrative logic—that is, the public tends to establish spatial identification through concrete architectural entities and historical narratives. In contrast, ‘Innovative Culture’ exhibits a distinctive ‘modern service-dependent’ perception pattern, with more sensitive emotional responses in the ‘tourist services’ and ‘public facilities’

dimensions, indicating that in modern cultural spaces, functional infrastructure has become a key variable reshaping the Sense of Place. Meanwhile, the emotional fluctuations of 'Ancient Capital Culture' in the 'visitor flow' and 'commercial environment' dimensions reflect the spatial crowding effects and commercialization erosion issues of historical neighborhoods under the tension between conservation and development.

In terms of environmental resistance dimensions, all cultural types exhibit significant low-value clustering in the dimensions of 'physical exertion,' 'weather/climate,' and 'commercial environment,' forming universal sentiment depressions. This reveals that the physiological limit constraints of tourism activities (physical exertion/climate) and the negative externalities from excessive commercialization are universal constraining factors that transcend cultural context. The existence of such 'common pain points' indicates that regardless of how distinctive regional cultural characteristics may be, the comfort of the physical environment and the health of the commercial ecosystem consistently serve as the fundamental thresholds affecting the public's overall cultural experience, as well as key intervention points for optimizing human–place relationships and enhancing the sustainability of cultural spaces.

To further characterize the polarity preferences of public perception toward different cultural spaces, this study conducted geospatial positioning analysis of sentiment attitudes (Figure 7). From a global perspective, the sentiment polarity of Beijing's cultural perception exhibits significant heterogeneous characteristics of 'large dispersion, small clustering.' Sentiment points are highly enriched in the old city core areas such as Dongcheng District and Xicheng District, forming the most prominent perception hotspot zones within the entire area, directly reflecting the strong projection of core-area high-density cultural carriers—such as the Forbidden City and Temple of Heaven representing 'Ancient Capital Culture,' and Tiananmen Square as the spiritual origin of 'Red Culture'—onto public psychological cognition. As geographic boundaries extend outward, sentiment distribution transitions from contiguous coverage in the central urban area to clustered agglomeration in functional expansion zones such as Haidian and Chaoyang, ultimately manifesting as discrete anchoring based on specific cultural nodes (e.g., the Jingxi Ancient Road, Zhoukoudian Site) in ecological conservation zones such as Mentougou and Fangshan, reflecting the pattern evolution of cultural perception from 'spatial flow' to 'spatial points.'

Within core functional zones, sentiment polarity exhibits significant complexity and volatility, presenting a state of 'perceptual high entropy.' This finding echoes the above conclusion that 'Ancient Capital Culture' and 'Beijing-Flavor Culture' obtain high sentiment values in the 'cultural heritage' dimension while exhibiting significantly low values in the 'commercial environment' and 'visitor flow' dimensions. Specifically, in historical-cultural neighborhoods such as Nanluoguxiang, Shichahai, and Dashilar, positive sentiment (green points) and negative sentiment (red points) are highly interwoven and overlapping. This indicates that on the one hand, the public derives an extremely high sense of cultural identity through profound genius loci and architectural aesthetics; on the other hand, the crowding sensation from high-density visitor flows and the loss of cultural authenticity from excessive commercialization transform into negative emotions within constrained physical spaces. This polarity coexistence pattern precisely portrays the psychological contestation of historical neighborhoods under the dual tension of heritage conservation and tourism development, validating that the negative externalities of the material environment have become a key factor constraining the construction of a positive Sense of Place in core zones.

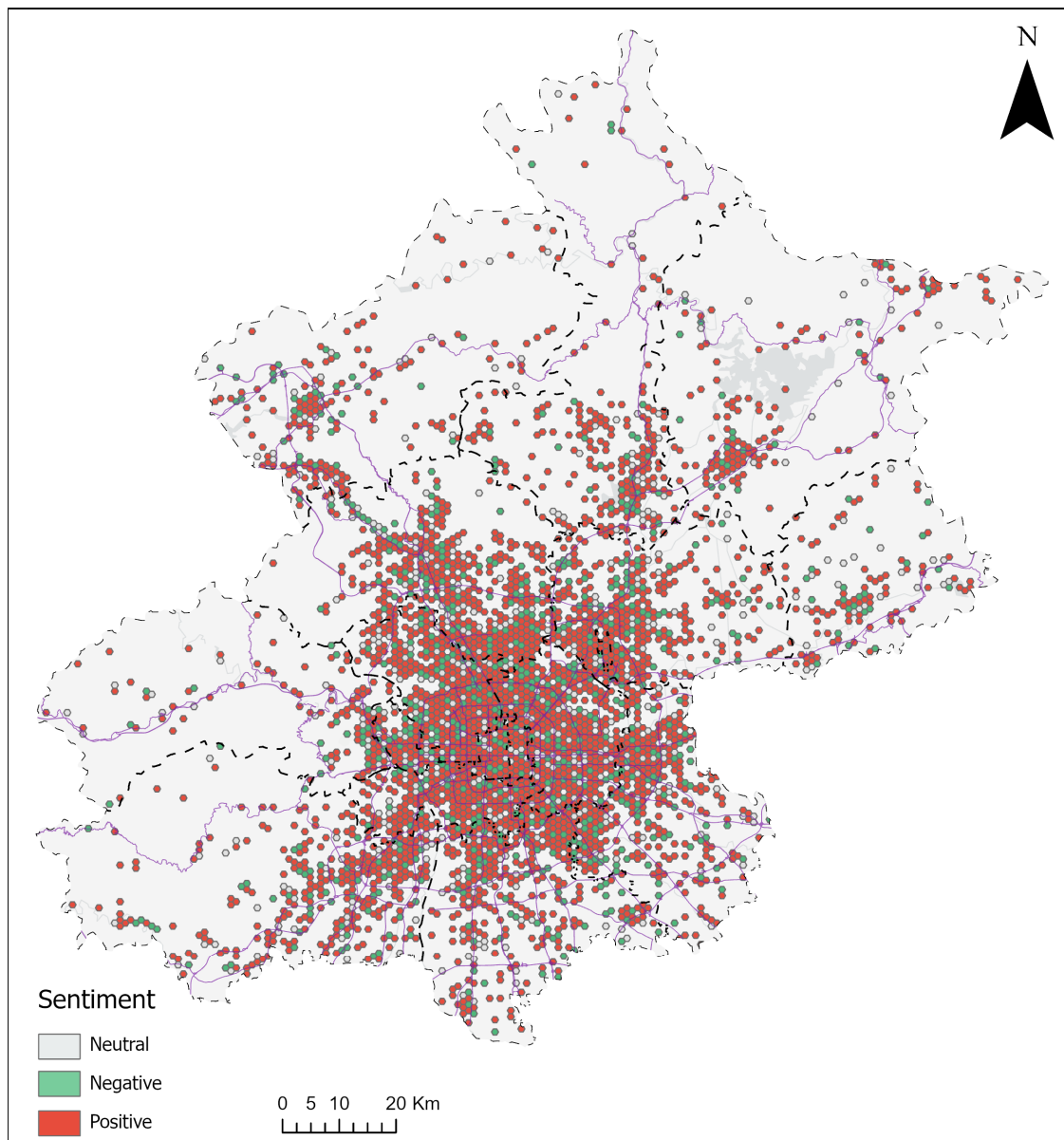


Figure 7. Spatial distribution of sentiment attitudes.

In functional expansion zones and outer suburban areas, sentiment distribution is more subject to the constraints of specific carrier functions and physical thresholds. The perception hotspots in the southeastern part of Haidian District and the central–western part of Chaoyang District are primarily concentrated in modern cultural landmarks such as the 798 Art District, the National Centre for the Performing Arts, and Zhongguancun. The clustered distribution of their positive sentiment corroborates the ‘modern service-dependent’ perception pattern exhibited by ‘Innovative Culture’ described above—that is, high-quality public facilities and tourist services exert a significant positive effect on enhancing the Sense of Place. In contrast, in western Beijing cultural resource distribution zones such as Fangshan and Mentougou, although sentiment points are predominantly positive evaluations with relatively pure polarity coloring, locally occurring negative polarity points often correspond to resistance dimensions such as ‘transportation convenience’ and ‘physical exertion.’ Particularly during the touring process of cultural carriers such as ancient road heritage sites, the physiological limit constraints of the physical environment and insufficient geographic accessibility remain fundamental bottlenecks affecting the depth of the public’s overall cultural perception.

3.2.3. Cultural Perception Pattern Recognition and Spatial Representation Based on Tensor Decomposition

Through non-negative tensor decomposition of the constructed four-dimensional tensor (four cultural types $\times$ 17 evaluation aspects $\times$ three sentiment polarities $\times$ five material cultural carrier categories), this study identified nine latent patterns characterizing urban cultural perception properties in the latent semantic space (Figure 7). The model goodness-of-fit reached 94.87% at $R = 9$, demonstrating that the model precisely captured the perception differences and semantic characteristics of different cultural types across geographic space. These patterns are not merely mathematical expressions of high-dimensional data but deeply delineate the dimensional coupling logic among cultural types, spatial carriers, and public psychological evaluations, revealing the complex perceptual heterogeneity in urban spatial production.

From the deep dimension of value guidance, Pattern 8 (Historical–Cultural Root-Seeking) and Pattern 5 (Administrative Space Quality) constitute the core tonality of capital cultural perception (Figure 8). In Pattern 8, Ancient Capital Culture and Red Culture achieve powerful coupling in political symbol spaces and imperial historical–cultural heritage spaces, with evaluation weights highly focused on historical cognition and emotional resonance, reflecting the public’s deep extraction of spaces as carriers of collective memory, embodying the sublimation of cultural value from physical landscape to spiritual narrative. Pattern 5, through high-standard spatial governance, transforms abstract ideology into concrete spatial order perception, with its highly positive evaluations of architectural aesthetics and spatial quality demonstrating the profound resonance between national narrative and individual perception in symbolic spaces.



Figure 8. Bubble matrix of latent patterns.

In the process of cultural revitalization and commercial intervention, Pattern 2 (Heritage–Innovation Dissonance) and Pattern 3 (Performance–Commercial Overload) precisely reveal the tension between commercialization logic and cultural authenticity. In Pattern 2, when innovative elements are rigidly implanted into imperial historical–cultural heritage spaces, the overall sentiment remains neutral, but significant negative coupling appears in cultural value and historical memory dimensions, characterizing a structural phenomenon of meaning stripping. Pattern 3 further reflects the diluting effect of capital expansion on cultural perception: in public cultural display and performance spaces, excessive commercial environment has become perceptual noise interfering with the public’s access to core cultural connotations. Such perceptual conflicts warn that excessive commercialization divorced from historical context is becoming one of the primary triggers for declining cultural perception evaluation.

Addressing the modernization transformation of culture, Pattern 1 (Beijing-Flavor Culinary Identification), Pattern 7 (Modern Beijing-Flavor Vitality), and Pattern 4 (Ancient Capital Arts and Cultural Amenities) present a positive prospect for cultural inheritance. Pattern 1 confirms that culinary experience constitutes the most resilient embodied threshold for the public to access traditional Beijing-Flavor Culture, with its high-weight distribution in modern commercial spaces demonstrating the suturing effect of everyday life practices on cultural identity. Pattern 7 and Pattern 4 reveal the revitalizing function of modern arts and cultural amenities for traditional residential and historical neighborhood spaces, effectively dissolving the historical alienation of cultural heritage through the reconstruction of traditional symbols via modern commercial narratives, achieving dual enhancement of perception intensity and emotional evaluation.

The ‘hard constraints’ of the material environment constitute bottleneck effects on cultural perception. In Pattern 6 (Heritage Touring Fatigue), the high-energy-level cultural weight of imperial historical–cultural heritage spaces is counteracted by high-load visitor flows and physical exertion, reflecting the phenomenon of diminishing marginal perceptual utility in top-tier heritage sites under conditions of saturated spatial carrying capacity. Pattern 9 (Neighborhood Environmental Adaptation) reveals the underlying logic of urban governance: in traditional residential and historical neighborhood spaces, the deficiency of transportation convenience, public facilities, and tourist services directly constrains the baseline of perception evaluation. Functional dissatisfaction triggered by infrastructure constraints forces the public’s evaluation to degrade from cultural aesthetics to material environment negotiation, forming material blockages along the cultural perception pathway.

In summary, the perception logic of Beijing’s capital culture exhibits hierarchical characteristics from core value-driven to safeguard condition-constrained dimensions. Future urban governance should transcend singular visual landscape production and shift toward pattern-feedback-based precision perception remediation: alleviating cognitive conflicts in Patterns 2 and 3 through ‘perception noise reduction,’ while eliminating the hard frictions blocking cultural value transmission by optimizing the physical environment shortcomings characterized by Pattern 9, thereby propelling urban space toward a systematic leap from material carrier to high-quality perception space.

Further integrating the specific spatial positional relationships of the nine patterns, as shown in Figure 9: these patterns are not merely factor clusters in the mathematical dimension but logical mappings of the public’s dynamic perception of cultural connotations within specific urban spaces. Overall, their spatial distribution characteristics exhibit pronounced perceptual heterogeneity and hierarchical regularities.

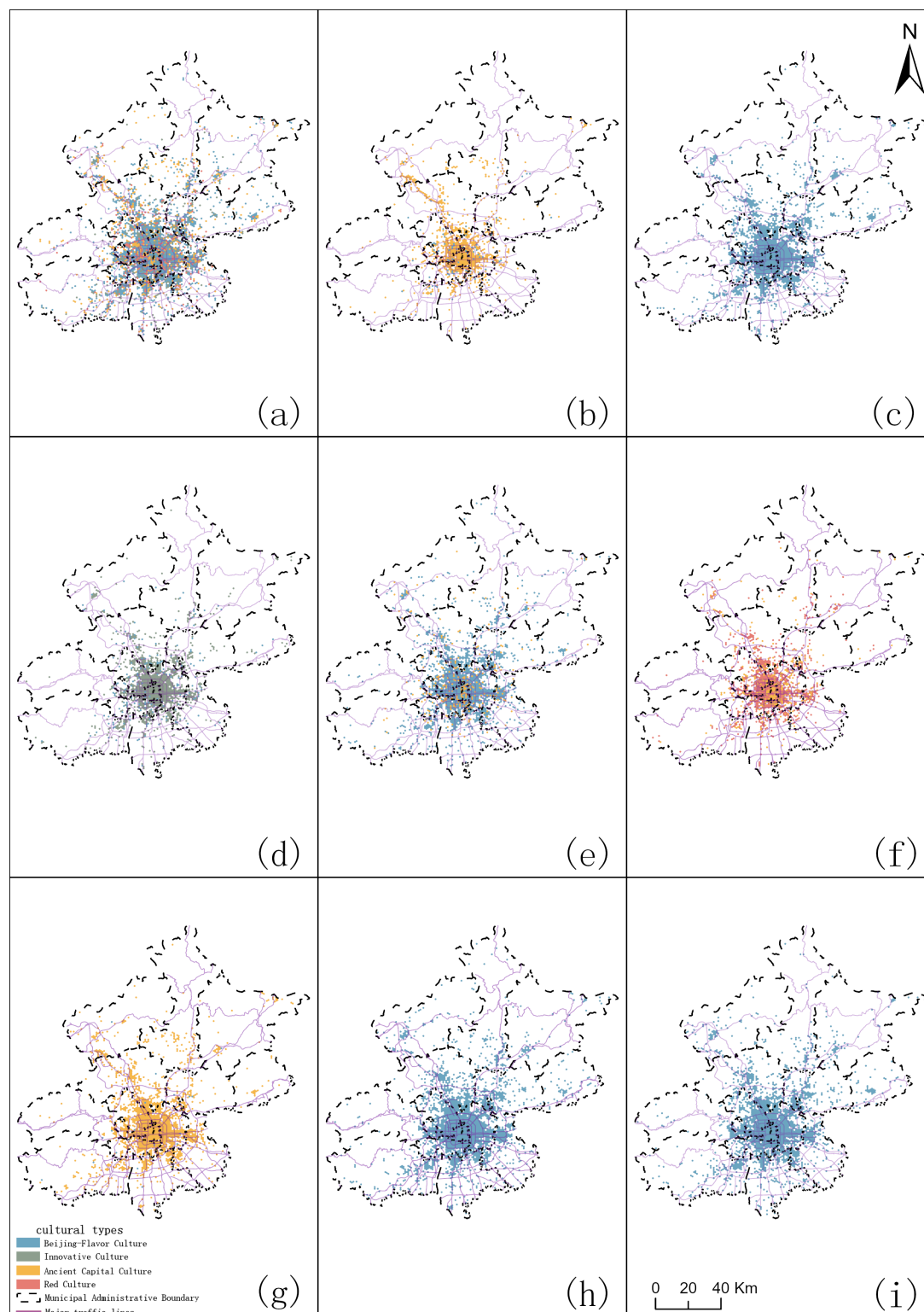


Figure 9. Spatial distribution of nine latent patterns.

First, in the spatial perception of core functional zones, a polarization characteristic of high value anchoring coexisting with perceptual saturation is exhibited. In Pattern 8 (Historical–Cultural Root-Seeking) and Pattern 5 (Administrative Space Quality), dimensions captured by the LLM such as ‘historical cognition,’ ‘emotional resonance,’ and ‘architectural aesthetics’ achieve powerful coupling within imperial historical–cultural heritage spaces and political symbol spaces. Spatial grid analysis reveals that such perception is

highly concentrated in the central urban area, demonstrating the powerful formative force of core symbolic spaces on public collective memory and national narratives. However, Pattern 6 (Heritage Touring Fatigue), which is emotionally negative, is also concomitantly distributed in the same area. The identified high-weight evaluation dimensions of ‘physical exertion’ and ‘visitor flow’ reveal the diminishing marginal perceptual utility of top-tier heritage sites under saturated spatial carrying capacity—that is, when the pressure of physical space surpasses the perception threshold, public evaluation rapidly shifts from cultural value extraction to physiological negative feedback.

Furthermore, mediating effects drive the active translation of traditional culture within the contemporary urban fabric. Spatial visualization results show that Pattern 1 (Beijing-Flavor Culinary Identification), Pattern 7 (Modern Beijing-Flavor Vitality), and Pattern 4 (Ancient Capital Arts and Cultural Amenities) constitute the vitality belt of capital perception. Pattern 1 exhibits extremely strong permeability spatially, proving that embodied cognition represented by cuisine is a resilient bond connecting traditional residential neighborhoods with modern commercial spaces. Pattern 7 and Pattern 4, through the embedding of modern arts and cultural formats at the edges of historical areas, achieve the modernization transformation of cultural dimensions. This dimensional coupling logic effectively dissolves the ‘sense of obsolescence’ of heritage sites, enabling traditional symbols to achieve aesthetic reproduction within modern consumption contexts and providing a functional darning pathway for the sustained activation of cultural perception.

This study also found that the maladjustment of commercial logic and infrastructure delineates conflict zones and safeguard baselines of perception. Spatial analysis clearly captures the perceptual alienation triggered by Pattern 3 (Performance–Commercial Overload) and Pattern 2 (Heritage–Innovation Dissonance) in specific zones. When the excessive expansion of the commercial environment or the rigid intervention of innovative elements deviates from the historical context of the space, the ‘commercial environment’ weight identified by the LLM abnormally amplifies, thereby generating significant semantic friction that shields the public from deep access to core cultural connotations. More fundamentally, Pattern 9 (Neighborhood Environmental Adaptation) outlines the perception boundary. This pattern reveals that regardless of how high the cultural energy level may be, the hard constraints of evaluation dimensions such as ‘transportation convenience’ and ‘public facilities’ consistently determine the baseline of perception evaluation. Infrastructure lag produces strong ‘material blockages,’ forcing the public’s attention to degrade from spiritual aesthetics to anxiety about basic environmental support.

In conclusion, the spatial representation of capital cultural perception is not a homogeneous overlay but a layered perception system composed of ‘core value-driven, mediating function-regulated, material condition-constrained’ components. This closed-loop research based on LLM fine-grained extraction and GIS spatial analysis demonstrates that the perception quality of capital culture depends not only on the energy level of the cultural carriers themselves but also on the semantic coordination and infrastructure support efficiency during the spatial utilization process. This provides refined scientific decision-making evidence for future urban governance to shift from ‘physical landscape production’ to ‘high-quality perception governance.’

3.3. Comprehensive Evaluation and Policy Guidance

Based on the above multi-dimensional analysis results, this study conducts a comprehensive evaluation of Beijing’s four major cultural types from three levels—overall perception level, aspect structural characteristics, and spatial distribution pattern—revealing the advantageous resources and shortcoming constraints of each cultural type in the construction of the National Cultural Center. It should be noted that the following policy

recommendations are derived from preliminary analysis based on 2019 data and require subsequent multi-temporal data validation to confirm their robustness and timeliness.

(1) Ancient Capital Culture: The overall sentiment score is at a medium–high level, with prominent cultural identification and historical value perception, making it the type with the strongest symbolic authority in the capital cultural perception system. Its advantages are concentrated in cultural heritage and historical cognition dimensions, forming high-intensity cultural perception hotspots based on world-class heritage sites such as the Forbidden City, the Temple of Heaven, and the Summer Palace. The main constraining factors are visitor flow overload and commercialization erosion, forming significant negative sentiment agglomeration zones in core heritage sites. We recommend optimizing heritage site capacity management and strengthen the coordination between commercial formats and historical–cultural atmosphere to enhance the sustainable perception experience of cultural heritage.

(2) Beijing-Flavor Culture: The overall sentiment score is the highest, with the widest perception coverage. It serves as the core carrier of public everyday cultural experience and the cultural type with the strongest adhesion to public life. Its advantages are embodied in the high perception popularity of culinary experience and lifestyle-oriented scenes, forming a region-wide permeable spatial distribution pattern. The main constraining factor is the dilution of cultural authenticity from excessive commercial intervention in certain traditional cultural carriers (e.g., hutong neighborhoods). We recommend strengthening the authenticity conservation and inheritance of traditional folk cultural spaces while maintaining the advantage of lifestyle-oriented perception, preventing commercialization from eroding cultural authenticity.

(3) Red Culture: The overall sentiment score is moderately high, with outstanding performance in the emotional resonance dimension and strong spiritual appeal, but with relatively limited perception coverage and frequency share. Its advantages are concentrated in the high emotional cohesion within political symbol spaces centered on Tiananmen Square. The main constraining factors are the high concentration of perception venues and insufficient daily life contact frequency, resulting in a weak broad-area perception foundation. The perception depth and accessibility of Red Culture in the public's daily life can be enhanced by expanding Red Culture dissemination scenarios and innovating Red Culture experience modalities.

(4) Innovative Culture: The overall sentiment score is at a medium level, with certain advantages in modern services and experience quality dimensions, but the cultural perception foundation still requires consolidation, and public cognition has not yet formed a stable perception paradigm. Its advantages are embodied in the revitalizing effect of creative cultural spaces on traditional historical spaces and the perceptual appeal of modern arts and cultural amenities for younger demographics. The main constraining factor is the insufficient degree of symbolization of perception carriers, lacking widely recognized iconic cultural symbols. Based on preliminary recommendations from current data, we suggest strengthening Innovative Culture brand building, promote the deep integration of technological innovation and cultural experience, and gradually cultivate an innovative cultural perception system with capital characteristics.

Taken together, Beijing's four major cultural types have formed differentiated competitive advantages and complementary patterns at the public perception level: Ancient Capital Culture possesses the strongest historical symbolic authority, Beijing-Flavor Culture has the broadest life permeability, Red Culture has the deepest emotional resonance effect, and Innovative Culture has the strongest modern vitality potential. The synergistic development and shortcoming reinforcement of the four cultural types constitute the core pathway for comprehensively enhancing the overall perception level of capital culture.

4. Discussion

4.1. Key Research Findings

Based on approximately 11.76 million social media text records, and through the construction of an LLM-driven agentic workflow and a multi-dimensional tensor decomposition framework, this study systematically revealed the structural characteristics, evaluation regularities, and spatial differentiation patterns of Beijing capital cultural perception. The key findings are as follows:

First, capital cultural perception exhibits a significant type-level hierarchical structure. Ancient Capital Culture (53.60%) and Beijing-Flavor Culture (28.56%) occupy dominant positions, together accounting for over 80% of perception share, while Red Culture and Innovative Culture together account for less than 20%. This ‘dual-core dominance, dual-wing weakness’ perception pattern reveals that in current capital cultural construction, historical and lifestyle-oriented cultural resources possess significant advantages in spontaneous public perception, whereas ideological culture and emerging cultural forms still have considerable room for improvement at the broad-area public cognition level.

Second, cultural perception exhibits pronounced aspect bias. The three aspect categories of cultural experience, culinary experience, and cultural atmosphere together account for 56.36% of total perception, reflecting a dominant perception logic of ‘scenarization, experientialization, lifestyle-orientation.’ In contrast, functional and knowledge-oriented aspects such as historical cognition, public facilities, and transportation convenience account for relatively low proportions, reflecting that the public’s demand for cultural experience has already transformed from mere knowledge acquisition toward immersive scenographic participation.

Third, material environmental constraints constitute common constraining factors across cultural types. Physical exertion, weather/climate, and commercial environment exhibit significantly low sentiment score clustering across all cultural types, indicating that the physiological limit constraints of tourism activities and the negative externalities of commercialization are key bottlenecks constraining the overall perception experience of capital culture, with their importance transcending the differentiability of cultural types.

Fourth, the nine latent perception patterns identified through tensor decomposition reveal the deep coupling mechanisms among cultural types, spatial carriers, evaluation aspects, and sentiment polarity, providing refined perception diagnostic evidence for urban governance. Among them, Historical–Cultural Root-Seeking (Pattern 8) and Beijing-Flavor Culinary Identification (Pattern 1) are the primary sources of positive sentiment production, while Heritage–Innovation Dissonance (Pattern 2) and Performance–Commercial Overload (Pattern 3) are the core causes of negative sentiment agglomeration, providing clear policy intervention directions for cultural space optimization.

4.2. Methodological Contributions

The methodological contributions of this study are reflected in the following three aspects:

(1) An agentic workflow framework integrating LLMs and ABSA was proposed, achieving a paradigm shift in cultural perception research from qualitative description to fine-grained quantitative analysis. Compared with traditional machine learning methods, the zero-shot classification strategy based on Qwen3-32B achieved over 90% classification accuracy without requiring large quantities of annotated data, significantly reducing the annotation cost and domain transfer difficulty of large-scale cultural text processing, thereby establishing the technical foundation for the scaled application of cultural perception research.

(2) The tensor decomposition method was introduced into cultural perception research, achieving higher-order coupling modeling of multi-dimensional semantic elements. Compared to traditional two-dimensional matrix analysis (e.g., LDA topic models, NMF non-negative matrix factorization), the four-mode tensor model can simultaneously characterize the interaction relationships among four dimensions—cultural type, evaluation aspect, sentiment polarity, and spatial carrier—achieving effective latent perception pattern extraction while retaining rich semantic information, providing a methodological reference for multi-dimensional modeling of complex human geographic phenomena.

(3) An integrated cultural perception evaluation system spanning from textual semantics to geographic space was constructed, promoting the exploratory transformation of GIS spatial analysis from a data-driven to an ‘AI + data’ dual-driven paradigm. By aligning the fine-grained sentiment data output by the LLM with GIS spatial coordinates, this study transcended the limitation of traditional GIS research that predominantly focuses on material spatial data processing, incorporating natural language semantic information into the geospatial analysis framework and broadening the data source scope and humanistic application depth of GIS.

4.3. Statistical Validation of Tensor Decomposition

To verify that the nine latent patterns extracted by CP decomposition (Section 3.2.3) represent genuine multi-way interactions rather than mere re-expressions of marginal frequencies, we conducted a marginal frequency dissolution experiment. The detailed numerical results of this experiment, including variance decomposition, stability statistics, factor matching, and rank sensitivity analysis, are provided in Appendix C.

An independence model was constructed under the assumption of complete dimensional independence:

$$T_{independent} = p_{cultural} \otimes p_{aspect} \otimes p_{polarity} \otimes p_{spatial} \times N \quad (5)$$

The variables in Equation (5) are defined as follows: where $T_{independent}$ denotes the expected tensor under the null hypothesis of complete dimensional independence; $p_{cultural}$, p_{aspect} , $p_{polarity}$, and $p_{spatial}$ represent the marginal probability distributions of cultural type, evaluation aspect, sentiment polarity, and spatial carrier, respectively; $N = 276,821$ is the total number of valid observations; and $\otimes$ denotes the tensor product (outer product), which combines the four marginal distributions into a complete four-dimensional grid of expected frequencies. Variance decomposition reveals that marginal frequencies account for 65.5% of the total variance, while the remaining 34.5% arises exclusively from multi-way interactions among the four dimensions. Cramér’s V reaches 0.8353, indicating a strong association that far exceeds what marginal distributions alone can explain.

CP decomposition ($R = 9$) on the residual tensor:

$$T_{residual} = T_{observed} - T_{independent} \quad (6)$$

where $T_{observed}$ is the original observed count tensor constructed from the geotagged social media data; $T_{independent}$ is the expected tensor under the independence model as defined in Equation (5); and $T_{residual}$ is the residual tensor that isolates the portion of the observed tensor not attributable to marginal frequencies. The non-zero structure of $T_{residual}$ directly reflects the genuine multi-way interaction effects among the four dimensions—cultural type, evaluation aspect, sentiment polarity, and spatial carrier—which are the primary target of CP tensor decomposition in this study.

CP decomposition on the residual tensor achieves a fit of $93.04\% \pm 0.31\%$, closely comparable to $95.73\% \pm 1.90\%$ for the original tensor. The average Factor Match Score

(FMS) between original and residual CP factors is 0.604, with three factor pairs exceeding 0.90 (pairs 1–9, 3–2, and 8–3)—corresponding to Patterns 1, 3, and 8 (Beijing-Flavor Culinary Identification, Performance–Commercial Overload, and Historical–Cultural Root-Seeking, respectively)—confirming that these key latent patterns are anchored in genuine interaction structures rather than marginal artifacts. The average FMS of 0.604 further indicates that some factors undergo structural reorganization after marginal effects are partialled out—demonstrating that CP decomposition captures information beyond simple marginal re-expression, rather than merely reproducing them.

NMF baselines, which collapse the four-order tensor into two-dimensional matrices, yield numerically higher fits (97.60–98.56%) but at the cost of destroying the four-dimensional coupling structure. This apparent superiority reflects the reduced structural constraint of matrix representations of NMF’s increased parametric flexibility in the compressed matrix space, not evidence of superior structural representation. CP retains the complete higher-order interactions—a trade-off essential for interpretability in cultural perception modeling. Stability analysis across 50 random initializations shows consistent fitting performance ($93.21\% \pm 1.90\%$, $CV = 2.04\%$), and rank sensitivity analysis confirms that $R = 9$ lies at the elbow point.

Collectively, these validation experiments substantiate that CP decomposition at $R = 9$ recovers genuine, stable, and interpretable higher-order cultural perception patterns—not spurious artifacts of marginal frequency distributions.

4.4. Limitations and Future Prospects

This study has the following limitations: first, data limitations. The Weibo data employed in this study exhibit user group bias—Weibo users cannot fully represent the cultural perception preferences of all Beijing residents and tourists, with younger users and higher-education groups potentially over-represented in the data. Furthermore, this study’s data cover only the year 2019, making it difficult to capture the temporal evolution patterns of perception influenced by major social events (e.g., the COVID-19 pandemic).

Second, methodological limitations: This study employs the locally deployed Qwen3-32B pre-trained model for zero-shot inference without task-specific fine-tuning. Although LLMs perform excellently in zero-shot classification, hallucination phenomena and contextual understanding deviations still exist, particularly for Beijing-specific historical-cultural vocabulary and dialect expressions. Moreover, while Qwen3 and DeepSeek-V3 are independently developed models with different training pipelines and proprietary data mixtures, both are trained on large-scale web corpora, so some overlap in public Chinese text sources is possible, though not publicly documented. Therefore, our cross-model agreement should be interpreted as a robustness check rather than a fully independent audit, and the final annotations should be treated as ‘model-assisted’ labels rather than ground truth.

Third, spatial analysis limitations: The existing analysis is primarily based on the geotagged coordinates of user posts, which do not fully equate to the user’s authentic cultural experience at that location, as some users may post texts related to specific locations without physically being present there.

Finally, policy recommendations require validation in subsequent research with updated data. The cultural perception spatial differentiation characteristics and nine latent perception patterns identified in this study provide valuable reference benchmarks for the precision governance of capital cultural space. However, the formulation of cultural policies should be established on the foundation of continuous monitoring of the dynamic evolution of cultural perception, rather than relying on single-time-point cross-sectional data. It is recommended that future research introduce multi-temporal social media data and, through temporal comparative analysis, reveal the dynamic evolution trajectory of

capital cultural perception, thereby providing more time-sensitive empirical support for policy recommendations.

Addressing the above limitations, future research can be extended in the following directions: (1) integrating multi-platform multi-source social media data (e.g., Douyin, Dianping, Ctrip) to broaden the demographic coverage and temporal span of data; (2) introducing multi-temporal data and combining temporal analysis to reveal the dynamic evolution patterns of capital cultural perception; (3) constructing domain-adaptive pre-trained models to enhance LLM performance in cultural perception vertical scenarios; (4) combining questionnaire surveys and field observation data for multi-angle verification of model output results.

5. Conclusions

This study constructed an urban cultural perception evaluation technical framework integrating large language models (LLMs), Aspect-Based Sentiment Analysis (ABSA), and tensor decomposition. Taking Beijing's four major capital cultural types as the research objects, a systematic analysis was conducted based on approximately 11.76 million geotagged social media texts. Core conclusions are drawn from three levels—policy implications, theoretical contributions, and methodological transferability:

(1) Policy Implications: Capital cultural perception exhibits a significant hierarchical imbalance structure, with Ancient Capital Culture and Beijing-Flavor Culture occupying absolutely dominant positions (82.16% combined), while the perception foundations of Red Culture and Innovative Culture are relatively weak. This finding provides empirical evidence for formulating differentiated cultural dissemination strategies, suggesting that the perceived presence of the latter two cultural types in public cognition be strengthened by expanding the everyday contact scenarios of Red Culture and the symbolic construction of Innovative Culture. It should be emphasized that the above policy recommendations are derived from preliminary analysis based on 2019 data and require subsequent multi-temporal data validation to confirm robustness and timeliness.

(2) Theoretical Contributions: This study advances the theoretical progress of cultural perception evaluation at three levels.

First, directly addressing RQ1, the proposed LLM-driven agentic workflow framework achieves a paradigm shift in cultural perception research from qualitative description to fine-grained quantitative analysis, demonstrating the effectiveness of LLMs in processing large-scale cultural texts under zero-shot conditions (accuracy > 90%, Cohen's $\kappa = 0.6827$), significantly reducing annotation costs and domain transfer difficulties.

Second, directly addressing RQ2, the systematic cross-analysis of cultural types, evaluation aspects, and spatial carriers reveals that Beijing's capital culture exhibits a significantly unbalanced hierarchical structure—Ancient Capital Culture (53.60%) and Beijing-Flavor Culture (28.56%) dominate public perception, while Red Culture and Innovative Culture remain relatively marginalized. More importantly, Cramér's $V = 0.8353$ confirms a strong non-random association among cultural types, evaluation dimensions, and sentiment polarity, while the four-mode tensor model further reveals higher-order interaction effects among cultural type, evaluation aspect, sentiment polarity, and spatial carrier—demonstrating that public emotional responses and spatial carrier preferences co-vary systematically across cultural types, far beyond random expectation.

Third, directly addressing RQ3, the introduction of tensor decomposition into cultural perception research, through a four-mode tensor model, identifies nine latent perception patterns with clear semantic interpretation and spatial directionality. These patterns are validated for stability ($93.21\% \pm 1.90\%$, CV = 2.04%) and demonstrated to be superior to matrix-based baselines (NMF) in preserving dimensional fidelity and interpretability,

providing a new theoretical perspective for understanding the structural differences in cultural perception and offering actionable insights for cultural space governance.

(3) **Methodological Transferability:** The technical framework of this study possesses strong generalizability and can be extended to cultural perception evaluation research in other historical–cultural cities. The integrated technical pathway of ‘LLM + ABSA Agentic Workflow+ Tensor Decomposition +GIS Spatial Analysis’ provides a reproducible and generalizable methodological paradigm for cities with rich cultural heritage resources to conduct cultural perception evaluation and spatial optimization research. Furthermore, the layered perception system of ‘core value-driven, mediating function-regulated, material condition-constrained’ revealed in this study also holds referential significance for the precision governance of cultural spaces in other cities.

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Appendix A. Complete Prompt Templates for the LLM-Based Agentic Workflow

This appendix presents the complete prompt templates employed across the four functional agents comprising the LLM-based agentic workflow described in Section 2.2.1. All templates were iteratively refined through a human-in-the-loop calibration process applied to a held-out annotation subset ($N \approx 500$) and subsequently deployed in batch inference using the locally deployed Qwen3-32B model. A Chain-of-Thought (CoT) reasoning strategy is embedded in each template: the model is explicitly instructed to compare the input sequentially against each feature criterion before producing its structured output, thereby reducing hallucination and improving decision consistency under zero-shot conditions. Prompts are presented in their final production versions; the rationale for each design decision is described in Section 2.2.1 of the main text.

Appendix A.1. Cultural Classification Agent

Agent 1 instantiates four parallel prompt templates—one per cultural category (Ancient Capital Culture, Red Culture, Beijing-Flavor Culture, Innovation Culture)—and applies them concurrently to each Weibo post. Each template executes two tightly coupled sub-tasks: (i) binary classification of whether the post pertains to the target cultural category (output: 0 or 1), and (ii) extraction of the material cultural carriers explicitly mentioned in the post. A CoT reasoning strategy is embedded by instructing the model to sequentially compare the input against each category-specific feature criterion before committing to a classification decision. The carrier extraction sub-task is conditioned on a positive classification outcome, forming a two-stage pipeline that reduces error propagation between

sub-tasks. The structured output (JSON array) is passed downstream to Agents 2 and 3 as shared context.

Appendix A.1.1. Ancient Capital Culture—Classification and Carrier Extraction

Prompt Template A1-1:

You are a semantic understanding assistant specializing in analyzing social media text. Capital culture includes: Ancient Capital Culture, Red Culture, Beijing-Flavor Culture, and Innovation Culture. Your task is twofold: Determine whether the text describes Ancient Capital Culture; extract the material cultural carriers that bear Ancient Capital Culture from the text.

Task 1: Ancient Capital Culture Determination: The main features of Ancient Capital Culture include:

Reflecting the history of Beijing as a long-term capital city, involving cultural forms such as artifacts, systems, and spirits;

Expressing feelings toward ancient culture, art, or lifestyles;

Demonstrating the integration of Beijing's regional culture and capital city culture;

Mentioning urban protection or cultural inheritance;

Describing important cultural heritage (such as the Central Axis, the Great Wall, the Grand Canal, etc.) (Note: Ancient Capital Culture does not involve traditional Old Beijing food, which belongs to Beijing-Flavor Culture.).

Rules: Strictly analyze based on the text content without making extensions or speculations; output 1 if it conforms to one or more features, otherwise output 0.

Task 2: Material Cultural Carrier Extraction Rules:

Only extract material cultural carriers explicitly mentioned in the text that conform to the features of Ancient Capital Culture.

The extracted carriers should be concrete, identifiable entities; do not extract abstract concepts or intangible cultural heritage.

If the text does not mention any material cultural carrier, return an empty list.

Output Format (JSON Array): [Culture Determination Result, "Carrier 1", "Carrier 2", ...].

Example Input 1: "Visited the Forbidden City today, and then climbed the Great Wall afterward. What a fulfilling day!" Example Output 1: [1, "Forbidden City", "Great Wall"].

Example Input 2: "Going shopping in Sanlitun today to experience the hustle and bustle of modern Beijing." Example Output 2: [0].

Constraints: Only output in JSON format; if it does not belong to Ancient Capital Culture, directly output [0]; when there is no carrier, only output the determination result.

Appendix A.1.2. Red Culture—Classification and Carrier Extraction

Prompt Template A1-2:

You are a semantic understanding assistant specializing in analyzing social media text. Capital culture includes: Ancient Capital Culture, Red Culture, Beijing-Flavor Culture, and Innovation Culture. Your task is twofold: Determine whether the text describes Red Culture; extract the material cultural carriers that bear Red Culture from the text.

Task 1: Red Culture Determination: The main features of Red Culture include:

Involving the history of the Communist Party of China regarding revolution, construction, and reform;

Mentioning Sinicized Marxism or Core Socialist Values;

Describing the historical significance of Beijing as the birthplace of New China;

Involving ideal and conviction education or Party history education to enhance national pride;

Expressing party-loving and patriotic sentiments during specific holidays (such as National Day, Army Day, Party Building Day, etc.);

Mentioning Red Culture sites (such as Tiananmen Square, the Peking University Red Building, Lugou Bridge, Fragrant Hills Revolutionary Memorial Land, etc.);

Describing the inheritance or promotion of Red Culture;

Rules: Distinguish it from the other three types of culture; output 1 if it conforms to one or more features, otherwise output 0.

Task 2: Material Cultural Carrier Extraction Rules: Same as the Ancient Capital Culture carrier extraction rules, with the target limited to material cultural carriers of Red Culture.

Output Format (JSON Array): [Culture Determination Result, "Carrier 1", "Carrier 2", ...].

Example Input: "Visited and paid respects to the Monument to the People's Heroes today, remembering the martyrs!" Example Output: [1, "Monument to the People's Heroes"].

Appendix A.1.3. Beijing-Flavor Culture—Classification and Carrier Extraction

Prompt Template A1-3:

You are a semantic understanding assistant specializing in analyzing social media text. Capital culture includes: Ancient Capital Culture, Red Culture, Beijing-Flavor Culture, and Innovation Culture. Your task is twofold: Determine whether the text describes Beijing-Flavor Culture; extract the material cultural carriers that bear Beijing-Flavor Culture from the text.

Task 1: Beijing-Flavor Culture Determination: The main features of Beijing-Flavor Culture include:

Linguistic characteristics of the Beijing dialect, such as the "Erhua" sound (r-coloring);

Traditional Old Beijing art forms, such as Peking Opera, storytelling (Pingshu), cross-talk (Xiangsheng), shadow puppetry, etc.;

Traditional Old Beijing snacks, such as Beijing roasted duck, fried sauce noodles (Zhajiangmian), bean juice (Douzhi), Jiaoquan, Luzhu, etc.;

Traditional Old Beijing folk customs, such as temple fairs, hutong culture, and courtyard (Siheyuan) living;

Traditional Old Beijing cultural venues and distinctive architecture, such as courtyards (Siheyuan), Longfu Temple, Yanjing Eight Palatial Handicrafts Museum, etc.

Rules: Strictly analyze based on the text content without making extensions or speculations; distinguish it from the other three types of culture; output 1 if it conforms to one or more features, otherwise output 0.

Task 2: Material Cultural Carrier Extraction Rules: Same as the Ancient Capital Culture carrier extraction rules, with the target limited to material cultural carriers of Beijing-Flavor Culture.

Output Format (JSON Array): [Culture Determination Result, "Carrier 1", "Carrier 2", ...].

Example Input: "Tried the bean juice today, almost threw up!" Example Output: [1, "bean juice"].

Appendix A.1.4. Innovation Culture—Classification and Carrier Extraction

Prompt Template A1-4:

You are a semantic understanding assistant specializing in analyzing social media text. Capital culture includes: Ancient Capital Culture, Red Culture, Beijing-Flavor Culture, and Innovation Culture. Your task is twofold: Determine whether the text describes innovation culture; extract the material cultural carriers that bear innovation culture from the text.

Task 1: Innovation Culture Determination: The main features of innovation culture include:

Innovative integration of Ancient Capital Culture, Red Culture, or Beijing-Flavor Culture with modern culture, such as cultural and creative products (Wenchuang), New Beijing Cuisine, New Peking Opera, etc.;

Describing the integration of culture with fields such as technology, tourism, sports, and finance, such as VR/AR exhibitions, digital museums, etc.;

Involving emerging cultural industries or cultural undertakings, such as cultural and creative industries, e-sports industries, trendy toy (Chaowan) industries, etc.;

Mentioning fashionable cultural activities or the development of art districts, such as livehouses, music festivals, art exhibitions, fashion weeks, concerts, etc.;

Describing multi-functional and composite cultural spaces, such as new reading spaces (e.g., Page One), drama bars, etc.;

Rules: Strictly analyze based on the text content without making extensions or speculations; distinguish it from the other three types of culture; output 1 if it conforms to one or more features, otherwise output 0.

Task 2: Material Cultural Carrier Extraction Rules: Same as the Ancient Capital Culture carrier extraction rules, with the target limited to material cultural carriers of innovation culture.

Output Format (JSON Array): [Culture Determination Result, "Carrier 1", "Carrier 2", ...].

Example Input 1: "798 Art Zone, so fashionable!" Example Output 1: [1, "798 Art Zone"].

Example Input 2: "Strolled through the Nanluoguxiang hutongs today and had a bowl of authentic Old Beijing fried sauce noodles." Example Output 2: [0].

Constraints: Only output in JSON format; if it does not belong to innovation culture, directly output [0]; when there is no carrier, only output the determination result.

Appendix A.2. Aspect-Based Sentiment Analysis (ABSA) Agent

Agent 2 receives the original Weibo text and the carrier list produced by Agent 1 and performs Aspect-Based Sentiment Analysis (ABSA) for each confirmed carrier-post pair. The model identifies which of the 17 pre-defined aspects are explicitly addressed in the text (six cultural perception aspects and eleven spatial perception aspects, as defined in Appendix B), extracts a concise opinion summary for each identified aspect, and assigns a three-class sentiment label (positive/negative/neutral). The 17 aspects operationalize the dual analytical framework of this study: Cultural perception covers cultural connotation, cultural atmosphere, cultural heritage, cultural experience, historical cognition, and emotional resonance; spatial perception covers natural landscape, humanistic landscape, architectural aesthetics, weather/climate, public facilities, visitor services, commercial environment, transportation accessibility, crowd density, physical exertion, and dining experience. The output is a structured JSON array of four-element tuples: [carrier, aspect, opinion summary, sentiment polarity].

Prompt Template A2:

Here is the precise academic English translation of your system prompt template for the Aspect-Based Sentiment Analysis task. The formatting, layout, structure, and JSON bracket configurations have been strictly maintained according to your original design:

[System Role] You are an AI assistant specializing in analyzing social media text. Your task is to extract evaluation opinions and sentiment analysis regarding specified aspects for given material cultural carriers.

Input Format:

Raw Social Media Text: [Original Text].

Extracted Material Cultural Carriers: ["Carrier 1", "Carrier 2", ...].

Specified Analysis Aspects (17 items in total, divided into two groups): [Cultural Perception Dimension]: Cultural Connotation, Cultural Atmosphere, Cultural Heritage, Cultural Experience, Historical Cognition, Emotional Resonance [Spatial Perception Dimension]: Natural Landscape, Cultural Landscape, Architectural Aesthetics, Weather and Climate, Public Facilities, Visitor Services, Commercial Environment, Traffic Convenience, Crowd Density, Physical Exertion, Dining Experience.

Extraction Rules:

For each extracted carrier, extract opinions or feelings related to the aforementioned aspects, and briefly summarize the perspective from the original text.

Perform sentiment analysis on each evaluation; the result must be chosen strictly from "Positive", "Negative", or "Neutral".

If no specific evaluation regarding an aspect of a carrier can be found, do not output any result for that aspect of the carrier.

If there are multiple distinct opinions regarding a single aspect, list them separately.

Output Format (JSON Array): [{"Carrier 1", "Aspect 1", "Evaluation 1", "Sentiment 1"}, {"Carrier 2", "Aspect 2", "Evaluation 2", "Sentiment 2"}, ...].

Constraints: Only output the result in JSON format; do not include any other explanations or commentaries. Ensure the JSON format is correct, using double quotes and separating the four elements with commas. If the text is too short or contains no explicit opinions, output an empty list []. If an aspect is not mentioned in the text, do not create an entry for that aspect; strictly extract according to the specified aspects.

Appendix A.3. Spatial Entity Extraction Agent

Agent 3 applies a multi-step quality-control pipeline to the raw carrier list from Agent 1. The pipeline proceeds through four sequential sub-tasks: (A3-1) spatial entity detection—each carrier phrase is classified as a geographically locatable entity (1) or not (0); (A3-2) toponymic normalization—confirmed spatial entities are standardized to their official names, resolving abbreviations, colloquialisms, and typographic errors via few-shot learning, thereby ensuring spatial uniqueness as required for downstream KDE analysis; (A3-3) site/sub-site classification and containment check—ambiguous carriers are distinguished as standalone geographic entities or sub-features within a parent attraction, with parent-child relationships recorded; (A3-4) Ancient Capital Culture carrier re-screening—a secondary semantic filter removes residual noise from the Ancient Capital Culture carrier list. Confirmed spatial entities are then assigned to one of five typological categories (A3-5) to serve as the carrier-type mode of the four-order tensor in Section 2.2.5.

Appendix A.3.1. Spatial Entity Detection

Prompt Template A3-1:

[System Role]

You are an expert in social media text carrier identification deeply rooted in Beijing capital culture. Your core task is: accurately identify whether a carrier phrase extracted from Beijing culture-related texts is a "real, concrete, and geographically locatable location on a map".

Identification Criteria (Priority: Positive Identification > Confusing Clarifications > Negative Identification):

Positive Identification (Output 1, identified if any single condition is met):

Scenic Areas/Parks: Forbidden City, Temple of Heaven Park, Beihai Park, Summer Palace, Badaling Great Wall, etc.

Cultural Venues: No. 93 Courtyard Museum, National Museum, Capital Museum, Beijing Planetarium, etc.

Characteristic Courtyards/Blocks: No. XX Courtyard, XX Hutong, XX Alley, XX Fang (e.g., Dashilanr).

Landmark Buildings: Tiananmen, Bird's Nest, Water Cube, Beijing Television Tower, Bell Tower/Drum Tower.

Other Locatable Cultural Sites: XX Former Residence, XX Temple/XX Monastery, XX Garden, XX Pavilion/Hall.

Fault Tolerance Rules: Minor modifications are allowed (e.g., "Forbidden City (The Palace Museum)"); typos are allowed (e.g., "Forbiden City", "Temple of Heven Park"); categories like "XX Courtyard/Hall/Museum" are all judged as 1.

Negative Identification (Output 0, strictly defined):

Architectural Parts/Components: Eaves of the Temple of Heaven, Steps of the Forbidden City, Bricks of the Great Wall.

Items/Exhibits: Longevity lanterns, porcelain, calligraphy and painting, VR equipment, cultural and creative products.

Activities/Behaviors: VR educational interaction, performances, temple fairs, parades, exhibitions.

Abstract Concepts: Folk culture, traditional techniques, cultural spirit, historical stories.

Hard Constraints:

Identification is based solely on the core semantics of the phrase, without obsessing over minor modifiers.

No association, no reasoning, no expansion, no error correction, and no rewriting.

The output must be only the pure digit 0 or 1, without any punctuation, spaces, or explanations.

Few-shot Examples:

Input: "Forbidden City" → Output: 1.

Input: "No. 93 Courtyard Museum" → Output: 1.

Input: "Eaves of the Temple of Heaven" → Output: 0.

Input: "Yandai Xiejie (Tobacco Pipe Oblique Street)" → Output: 1.

Input: "VR educational interaction" → Output: 0.

Appendix A.3.2. Toponymic Normalization/Name Alignment

Prompt Template A3-2:

[System Role]

You are an expert specializing in social sensing computing and GIS spatial data cleaning, skilled at normalizing and aligning place name carriers extracted from high-noise social media texts (such as Weibo) to output standard geographic entity names.

[Task]

After self-learning by referencing the alignment results in the provided training set, perform place name normalization and alignment on the input carrier list. The output results must achieve spatial uniqueness (the highest criterion).

[Execution Logic]

Step 1: Spatial Entity Recognition: Determine whether the term refers to a concrete, locatable geographic space (scenic area, building, street, station, block).

Step 2: Standard Name Alignment:

(a) Alias/Abbreviation Normalization: Map pronouns and abbreviations to official standard full names (e.g., National Museum -> National Museum of China).

(b) Homophone/Visual Error Correction: Correct typos in colloquial language (e.g., Nanluo Guxiang -> Nanluoguxiang).

(c) Traditional to Simplified Conversion: Always convert traditional Chinese characters into simplified Chinese.

Step 3: Non-spatial Items Keep Intact: If the target is not a specific location (food, crowds, verbs, generalized plants, etc.), or contains numbers but its specific spatial location cannot be determined, it must be output exactly as it is.

[Output Constraints]

Only output the processed name list, one per line, in the exact same order as the input. Strictly forbidden to output any introduction, explanation, notes, or table symbols.

Few-Shot Examples:

Input: Forbidden City → Output: Palace Museum.

Input: National Museum → Output: National Museum of China.

Input: Nanluo Guxiang → Output: Nanluoguxiang.

Input: Dashilanr → Output: Dashilanr Historical and Cultural Block.

Input: Beihai → Output: Beihai Park.

Input: Copper pot hot pot → Output: Copper pot hot pot (Non-spatial item, output as is).

Input: No. 2 Courtyard → Output: No. 2 Courtyard (No context, output as is).

Appendix A.3.3. Site/Sub-Site Classification and Containment Check

Prompt Template A3-3:

[System Role]

You are an annotation assistant specializing in the semantic analysis of geographic entities, required to perform a two-step refined screening on carrier phrases:

Step 1: Location/Non-Location Differentiation.

Key characteristics determined as a location:

Explicitly refers to a place or a complete building within a specific location, such as the Meridian Gate of the Forbidden City, the Temple of Heaven, the White Dagoba of Beihai Park, etc.

Characteristics easily misidentified as locations:

Related activities, items, merchandise, or vague descriptions of a location (e.g., Forbidden City Calendar, Forbidden City Lantern Festival, Temple of Heaven Temple Fair).

Only partial characteristics of a location (e.g., red walls and green tiles, Jingshan's cats, the eaves of the Forbidden City).

Output: Meets the main location characteristics → 1; Otherwise → 0.

Step 2: Containment Relationship of Buildings within Scenic Spots (Executed only when Step 1 outputs 1).

Key characteristics determined as a complete building within a scenic spot:

Explicitly a complete building inside a location, such as the Treasure Gallery, the Meridian Gate of the Forbidden City, the White Dagoba of Beihai Park, etc.

Characteristics easily misidentified as a building within a scenic spot:

Complete independent scenic spots, such as the Palace Museum, the Temple of Heaven, Jingshan Park, etc.

The same type of location shared by multiple scenic spots (without containing the modifier that implies it belongs to a specific scenic spot), such as a lakeside pavilion, a pagoda, etc.

Output Format (JSON Array): If it is a building within a scenic spot → [1, "The corresponding Beijing scenic spot"]; Otherwise → [0].

Examples:

Input: "Treasure Gallery" → [1, "Palace Museum"].

Input: "Palace Museum" → [0].

Input: “Eaves of the Temple of Heaven” → [0].

Appendix A.3.4. Ancient Capital Culture Carrier Re-Screening

Prompt Template A3-4:

[System Role]

You are a semantic understanding assistant specialized in analyzing social media texts, performing a secondary precise screening of Ancient Capital Culture carriers to eliminate noise from the initial extraction round.

Key Characteristics of Ancient Capital Culture:

Reflects the history of Beijing as a long-term capital, involving cultural forms such as artifacts, institutions, and spirit.

Expresses feelings towards ancient culture, art, or lifestyles.

Showcases the integration of Beijing’s regional culture with capital culture.

Mentions urban preservation or cultural heritage transmission.

Describes major cultural heritage sites (such as the Central Axis, the Great Wall, the Grand Canal, etc.).

(Note: Does not involve traditional Old Beijing food, which belongs to Beijing-Flavor Culture.).

Thinking Rules: Compare against the characteristics of Ancient Capital Culture item by item. If it conforms to one or more → output 1; otherwise → output 0.

Constraint Rules: Strictly based on the text content, making no extensions or speculations; do not output explanations or comments, only output 0 or 1.

Examples:

Input: “Dengshikou” → 1.

Input: “Window” → 0.

Input: “Pen” → 0.

Appendix A.3.5. Material Cultural Carrier Typology Standardization

Each confirmed spatial carrier is assigned to one of five mutually exclusive typological categories based on a priority-ordered classification rule: (1) Royal Historical and Cultural Heritage Space; (2) Traditional Residential and Historic District Space; (3) Public Cultural Display and Performing Arts Space; (4) Political Symbol and Red Cultural Space; (5) Modern Commercial and Urban Leisure Cultural Space. This typological labelling serves as the carrier-type mode (fifth dimension) of the four-order tensor constructed in Section 2.2.5.

Prompt Template A3-5:

[System Role]

You are an annotation assistant engaged in the standardized processing of cultural heritage data. Your task is to classify the “Cultural Carrier Name” in the input data, add a new column named “Carrier Classification”, and write the classification result into this column in JSON format.

Classification System (Strictly limited to the following five categories):

Royal History and Cultural Heritage Space: Palaces, royal gardens, sacrificial buildings, world heritage sites.

Traditional Residential and Historical Block Space: Hutongs, courtyards (Siheyuan), historical blocks, traditional residential areas.

Public Cultural Exhibition and Performing Arts Space: Museums, art galleries, theaters, bookstores, cultural venues.

Political Symbolism and Red Culture Space: Memorial halls, revolutionary sites, national political spaces.

Modern Commercial and Urban Leisure Culture Space: Business districts, commercial complexes, creative parks, leisure and entertainment spaces.

Classification Rules (Based on the Core Functional Attribute Priority Principle):

If an item matches multiple categories, select only the category corresponding to its “most primary function”.

Priority order: Political Symbolism > Historical Heritage > Cultural Exhibition > Residential > Commercial.

Each carrier can belong to only one category.

Output Requirements:

Add a new column named “Carrier Classification” on the basis of the original data. The content must be in JSON format, containing only one key-value pair: {“Specific Category Name”}.

Do not change the original fields or their content; do not output explanations, descriptions, or extra text.

Example:

Input → Cultural Carrier Name: Forbidden City/Palace Museum.

Output Added Column → Carrier Classification: {“Royal History and Cultural Heritage Space”}.

Appendix A.4. Self-Correction and Reflection Agent

Agent 4 serves as the quality-assurance closure of the agentic workflow and implements a structured self-reflection mechanism with a dedicated prompt template. Upon receiving the consolidated outputs from Agents 1, 2, and 3—covering cultural classification, ABSA results, and spatial entity extraction—Agent 4 executes five sequential consistency checks: (A) carrier–cultural-category semantic alignment; (B) sentiment–aspect–carrier triplet coherence; (C) spatial entity uniqueness verification; (D) inter-cultural-type mutual exclusivity; and (E) carrier–geographic-typology consistency. When a logical inconsistency is detected, Agent 4 triggers a selective re-invocation of the relevant upstream agent (Agent 1, 2, or 3) with the original input and the flagged output, prompting the model to re-examine and correct its prior decision. This self-reflection mechanism is applied through random sampling across processing batches: after every five batches of approximately one million posts, 500 records are randomly drawn for human annotation review; the resulting feedback is used to refine the prompts of the implicated agents and to recalibrate the inconsistency-detection threshold. This iterative human-in-the-loop process mitigates LLM hallucination and ensures that classification consistency and structured output compliance are maintained across the full corpus of approximately 10.41 million pre-processed posts.

Appendix A.4.1. Consistency Check and Re-Reasoning Prompt

Prompt Template A4:

[System Role]

You are an AI assistant specializing in the logical verification and self-correction and reflection of agent workflow outputs.

Your responsibility is to detect logical consistency across the outputs generated by Agents 1, 2, and 3, and trigger the necessary re-reasoning to correct potential errors.

[Input Information]

Original Social Media Text: [cleaned_content].

Cultural Type Identification Result (Agent 1): {“Ancient Capital Culture”: [Identification Value, [Carrier List]], “Red Culture”: [...], “Beijing-Flavor Culture”: [...], “Innovation Culture”: [...]}.

Sentiment Analysis Result (Agent 2): [[Carrier, Evaluation Aspect, Evaluation Content, Sentiment],...].

Geographic Carrier Extraction Result (Agent 3): {"Location Identification": [...], "Place Name Alignment": [...], "Type Classification": [...]}.

[Core Task: Logical Consistency Detection].

You must sequentially execute the following five checks. If any single check triggers an inconsistency, the validation is considered failed:

Detection A: Carrier-Cultural Type Consistency.

Check: Whether the extracted carrier semantically matches the identified cultural type.

Inconsistency Example: Carrier: "Luzhu" + Cultural Type = "Innovation Culture" → Inconsistent (Luzhu belongs to Beijing-Flavor Culture). Carrier: "Deyun Club" + Cultural Type = "Ancient Capital Culture" → Inconsistent (Deyun Club belongs to Beijing-Flavor Culture).

Inconsistency Output: {"result": 0, "error_type": "carrier_culture_mismatch", "flagged_items": [{"Carrier", "Identified Cultural Type", "Correct Cultural Type"}]}.

Detection B: Sentiment-Evaluation Aspect-Physical Carrier Triplet Consistency.

Check: Whether the sentiment polarity output by ABSA matches the typical evaluation aspects of the cultural type to which the physical carrier belongs.

Inconsistency Example: Ancient Capital Culture carrier "Great Wall" + Evaluation Aspect = "Dining Experience" → Questionable (requires contextual judgment based on the text).

Inconsistency Output: {"result": 0, "error_type": "sentiment_aspect_mismatch", "flagged_items": [{"Carrier", "Evaluation Aspect", "Sentiment"}]}.

Detection C: Place Name Alignment Spatial Uniqueness Detection.

Check: Whether the carrier after place name alignment satisfies spatial uniqueness (i.e., multiple aliases for the same location do not coexist).

Inconsistency Example: "Forbidden City" and "Palace Museum" appear simultaneously as alignment results in the same text → Duplicate, needs to be merged.

Inconsistency Output: {"result": 0, "error_type": "spatial_duplicate", "flagged_items": [{"Original Item", "Aligned Name"}]}.

Detection D: Cultural Type Mutual Exclusivity Detection.

Check: Whether multiple cultural types within the same text satisfy mutual exclusivity constraints (i.e., no logically contradictory co-existence of multiple types).

Inconsistency Example: Text: "Beijing roast duck in Sanlitun" → Judged as Beijing-Flavor Culture + Innovation Culture → Acceptable (conforms to integration characteristics). Text: "Passed by Tiananmen today" → Judged as Ancient Capital Culture + Red Culture → Acceptable (Tiananmen simultaneously carries dual attributes).

Pass Rule: The combination of cultural types corresponding to a carrier must satisfy: the same carrier cannot simultaneously serve as the core carrier for both Ancient Capital Culture (historical heritage attribute) and Innovation Culture (modern integration attribute), unless the text explicitly reflects an integrated narrative.

Inconsistency Output: {"result": 0, "error_type": "cultural_type_conflict", "flagged_items": [{"Conflicting Type Combination"}]}.

Detection E: Carrier-Geographic Type Consistency.

Check: Whether the type classification of the geographic carrier matches the semantic meaning of the carrier.

Inconsistency Example: "Tiananmen Square" → Classification result is "Modern Commercial and Urban Leisure Culture Space" → Inconsistent (should be "Political Symbolism and Red Culture Space").

Inconsistency Output: {"result": 0, "error_type": "carrier_type_mismatch", "flagged_items": [{"Carrier", "Current Classification", "Correct Classification"]]}.

[Output Format]

When all detections pass:

JSON

```
{
  "result": 1,
  "errors": []
}
```

When any detection fails:

JSON

```
{
  "result": 0,
  "errors": [
    {
      "error_type": "Error Type (see A-E above)",
      "original": "Original output content",
      "expected": "Correct output content or correction description",
      "confidence": "High/Medium/Low (based on textual evidence strength)"
    }
  ]
}
```

[Re-reasoning Trigger Mechanism]

When result=0, you must simultaneously output the corrected complete record:

JSON

```
{
  "result": 0,
  "errors": [...],
  "corrected_record": {
    "cultural_classification": {...}, // Corrected cultural type identification
    "absa_result": [...],           // Corrected sentiment analysis result
    "spatial_result": {...}         // Corrected geographic carrier result
  }
}
```

[Constraints]

Output correction results only when internal textual evidence is explicit; do not extrapolate using external knowledge.

If detection fails but the textual evidence is insufficient to support a deterministic correction, output result = 0 and specify "Manual review recommended" within the corrected_record.

The output format must strictly be JSON, without any explanatory text.

Confidence assessment standard: High = direct evidence exists in the text; Medium = requires inference based on context; Low = inferred solely based on statistical probability.

Appendix A.4.2. Human-in-the-Loop Calibration Mechanism

In addition to the automated self-correction loop (A4-1), the Agent 4 workflow incorporates a human-in-the-loop (HITL) calibration mechanism to ensure robustness at scale. After every five processing batches (~one million posts each), a random sample of 500 records is drawn for manual annotation review by domain experts. Annotators

verify the outputs of all three upstream agents (Agents 1, 2, and 3) and flag any remaining inconsistencies. The aggregated annotation feedback serves two purposes: (i) recalibrating the error-type taxonomy used in A4-1, and (ii) updating the few-shot exemplars embedded in the upstream prompts to suppress recurring error patterns. This iterative calibration was conducted over five rounds during the pilot phase, yielding the final prompt versions presented in Sections A.1–A.3 above.

Note on Prompt Engineering and CoT Design

All prompts in this workflow incorporate an implicit Chain-of-Thought (CoT) reasoning strategy. Specifically, each template instructs the model to compare the input text sequentially against each feature criterion before producing the final structured output. This encourages multi-step reasoning rather than surface-level pattern matching. For multi-task prompts (Agent 1 and A3-3), the CoT is structured as a two-stage pipeline: the model first executes the binary classification decision; then, conditioned on a positive outcome, proceeds to the carrier extraction or containment-analysis sub-task. This sequential conditioning reduces error propagation between sub-tasks. Few-shot exemplars drawn from the Beijing cultural context are embedded in all templates to anchor the model’s output distribution and suppress formatting non-compliance. Prompt versions were iteratively refined over five human-in-the-loop calibration rounds, with each round targeting specific error categories identified in the sampled annotation review (see Section 2.2.1).

Appendix B. Operational Definitions of Evaluation Dimensions, Weights by Entropy Weight Method and Algorithm Details

This appendix presents the following contents: (1) operational definitions for the 17 evaluation aspects (Table A1); (2) objective weight values of each aspect calculated via the entropy weight method (Table A2); (3) hyperparameter configuration for CP tensor decomposition (Table A3); (4) methodological comparison framework among CP decomposition, LDA and NMF (Table A4). As supplementary explanations for the methodology and results in the main text, all contents are designed to improve the reproducibility of this research.

Table A1. Operational definitions, typical trigger words, and literature support for 17 evaluation aspects.

No.	Evaluation Aspect	Evaluation Dimension	Operational Definition	Typical Trigger Words	Cross-Cultural Applicability
1	Cultural Experience	Cultural Value and Heritage	It refers to the public’s evaluation of the overall experience quality generated by participating in or perceiving cultural activities, venues and projects, which encompasses the sense of acquisition, immersion and satisfaction with cultural contents.	Experience, perception, visit, sightseeing, appreciate, view, experience, impression, atmosphere, immersion	Applicable to all four categories of culture, this is a universal dimension with the highest evaluation frequency. Ancient Capital Culture highlights heritage tour experiences, whereas Innovative Culture lays emphasis on interactive participation experiences, which should be differentiated in light of the context.
2	Culinary Experience	Service Facilities and Convenience	It represents the public’s perception and evaluation of Beijing’s distinctive cuisines, catering venues and food cultural customs, covering food taste, dining environment, service quality and identification with food culture.	Delicacies, Peking duck, noodles with soy bean paste, Luzhu, Douzhi, restaurants, snacks, time-honored brands, food, delicious, unpalatable	It is mainly concentrated in Beijing-Flavor Culture, accounting for 81.6%, and occasionally appears in Ancient Capital Culture and Innovative Culture. Dialectal food terms such as “Erguotou” and “Baodu” are strong indicators of Beijing-Flavor Culture.

Table A1. Cont.

No.	Evaluation Aspect	Evaluation Dimension	Operational Definition	Typical Trigger Words	Cross-Cultural Applicability
3	Cultural Atmosphere	Cultural Value and Heritage	It refers to the public's perception of the overall cultural atmosphere, historical ambience, regional characteristics or contemporary spirit prevailing in specific cultural spaces, highlighting the appeal of the intangible cultural traits and genius loci of the spaces.	Atmosphere, ambience, feeling, charm, heritage, primitive simplicity, sense of history, cultural vibe, style, distinctive appeal	It is distributed across all four types of culture. Ancient Capital Culture leans toward "historical atmosphere", Red Culture toward "spiritual atmosphere", and Innovative Culture toward "modern creative atmosphere". Neutral scores are difficult to attribute, so reference to cultural type labels is required.
4	Natural Landscape	Natural Landscape and Environment	It refers to the public's aesthetic perception and evaluation of natural environmental elements inside and around cultural spaces, such as mountains, waters, vegetation and weather, which reflects the contribution of natural ecology to the overall quality of cultural sites.	Scenery, landscape, greening, mountains and rivers, lakes, trees, flowers, mountain scenery of the Great Wall, lake surface of the Summer Palace, natural scenery	It occurs frequently in Ancient Capital Culture (imperial gardens) and Red Culture (mountain landmarks). Descriptions of natural elements shall be distinguished from those of cultural elements, and purely natural descriptions are classified into this category.
5	Cultural Connotation	Cultural Value and Heritage	It refers to the public's cognition and evaluation of the spiritual core, historical significance, cultural value and knowledge depth embodied by a certain cultural type, emphasizing the understanding and appreciation of the in-depth implications of cultural objects.	Connotation, spirit, significance, value, cultural heritage, inheritance, historical mission, essence, intrinsic value	It is frequently adopted in Red Culture (ideological connotation) and Ancient Capital Culture (historical civilization connotation). It should not be confused with "cultural experience", as the former emphasizes cognitive understanding while the latter focuses on experiential feelings.
6	Commercial Environment	Service Facilities and Convenience	It refers to the public's evaluation of commercial facilities, consumption environment, business formats and commercialization degree surrounding cultural venues, including negative feedback on the erosion of cultural authenticity caused by excessive commercialization.	Commerce, consumption, shopping, shops, vendors, over-development, scenic commodification, commercialization, souvenir selling	Negative emotions are mostly found in Ancient Capital Culture (commercialization of scenic areas) and Beijing-Flavor Culture (excessive commercialization of traditional blocks), while positive emotions appear in Innovative Culture (modern commercial supporting facilities).
7	Pedestrian flow	Experience Quality and Comfort	It refers to the public's perception of pedestrian density in cultural spaces, which mainly reflects the impact of crowding on touring experience, and most related feedback is negative.	Overcrowded, crowded, a sea of people, queuing, congested, dense pedestrian flow, no standing space, full of visitors during holidays	It mainly occurs at popular scenic spots of Ancient Capital Culture such as the Forbidden City and the Great Wall, and occasionally appears in holiday scenarios of Beijing-Flavor Culture. The vast majority of its emotional polarity is negative (over 85%).

Table A1. Cont.

No.	Evaluation Aspect	Evaluation Dimension	Operational Definition	Typical Trigger Words	Cross-Cultural Applicability
8	Physical Exertion	Experience Quality and Comfort	It refers to the public's perception of physical strength consumption and fatigue caused by walking distance, climbing height, touring duration and other factors during visits to cultural sites, which is generally correlated with negative emotions.	Tired, long walks, mountain climbing, sore feet, too far, physical strength, exhausted, sore legs, lengthy walking, high physical exertion	It frequently occurs at landmarks of Ancient Capital Culture such as the Great Wall (high physical exertion from climbing), the Palace Museum (large area) and the Summer Palace, and also appears in hutong touring scenarios of Beijing-Flavor Culture.
9	Emotional Resonance	Experience Quality and Comfort	It refers to the emotional projection, spiritual inspiration and value recognition generated during people's visits to cultural venues, including in-depth emotional experiences such as patriotism, nostalgic memories and cultural pride.	Moving, stunning, resonance, proud, patriotic, tearful, touched, recollection, patriotism, emotional connection	This dimension accounts for the largest proportion in Red Culture, manifested as patriotic sentiments. It is reflected as regional nostalgia in Beijing-Flavor Culture, and as cultural identity and profound historical sentiment in Ancient Capital Culture.
10	Architectural Aesthetics	Cultural Value and Heritage	It refers to the public's aesthetic evaluation of the architectural form, spatial layout, decorative art and visual beauty of cultural venues, emphasizing the artistic value of buildings as cultural carriers.	Architecture, palaces, temples, design, appearance, ancient buildings, carvings, painted decorations, architectural style, magnificent, exquisite	It is mainly reflected in Ancient Capital Culture (imperial architecture) and Red Culture (memorial architecture). The aesthetics of modern architecture can also be found in Innovative Culture, such as the National Centre for the Performing Arts.
11	Historical Cognition	Cultural Value and Heritage	It refers to the public's cognitive perception of specific historical events, figures and backgrounds embodied in cultural venues, emphasizing the acquisition and learning of historical knowledge.	History, dynasties, emperors, eras, historical records, ancient times, historical events, the Qing Dynasty, the Ming Dynasty, modern history	This dimension occurs most frequently in Ancient Capital Culture (imperial history) and Red Culture (modern revolutionary history). A distinction should be made between the learning of historical knowledge (this dimension) and historical emotional identification (emotional resonance dimension).
12	Weather and Climate	Experience Quality and Comfort	It refers to the public's perception and evaluation of weather conditions (temperature, precipitation, wind and sand, haze, etc.) during visits, reflecting the impact of Beijing's specific climatic conditions on cultural experiences.	Weather, rain, wind, sandstorm, haze, too hot, too cold, temperature, intense sunlight, cold weather	It exists across all four types of culture and mainly appears at outdoor cultural sites. Sand and dust in spring and high temperature in summer in Beijing are frequent triggers for negative experiences.

Table A1. Cont.

No.	Evaluation Aspect	Evaluation Dimension	Operational Definition	Typical Trigger Words	Cross-Cultural Applicability
13	Public Facilities	Service Facilities and Convenience	It refers to the public's evaluation of public infrastructure inside and around cultural venues, including restrooms, lounge areas, signage systems, barrier-free facilities and charging facilities.	Toilets, restrooms, lounge areas, seats, signs, signboards, barrier-free access, facilities, basic supporting amenities	This dimension is reflected in all four types of culture. Negative comments mainly focus on core scenic spots of Ancient Capital Culture due to insufficient restrooms and lounge areas, while public facilities in venues of Innovative Culture receive generally favorable evaluations.
14	Cultural Heritage	Cultural Value and Heritage	It refers to the public's perception, evaluation and awareness of inheritance regarding tangible cultural heritage (architecture, cultural relics, historical sites, etc.) and intangible cultural heritage (crafts, folk customs, etc.).	Heritage, cultural relics, historic sites, ruins, world heritage, traditional crafts, intangible cultural heritage, inheritance, historical remains	This dimension is highly concentrated in Ancient Capital Culture, accounting for 68.4%. Different from "cultural connotation", this dimension focuses more on the perception of physical relics rather than the understanding of the spirits they embody.
15	Transportation Convenience	Service Facilities and Convenience	It refers to the public's evaluation of the accessibility (subway, bus, parking, roads) of cultural venues, as well as perceptions of internal traffic organization within scenic areas.	Subway, bus, parking, traffic jam, transportation, accessible, taxi ride, distance, far or not	It appears in all four categories of culture. Negative traffic evaluations are relatively high for suburban cultural sites (e.g., Zhoukoudian, remote sections of the Great Wall); accessibility evaluations for Ancient Capital Culture and Red Culture venues in urban core areas are generally favorable.
16	Human Landscape	Natural Landscape and Environment	It refers to the public's overall perception of cultural landscapes shaped jointly by human historical activities and natural environments, such as ancient villages, historical streets, traditional settlements and ancient and famous trees.	Hutongs, ancient streets, ancient villages, lanes and alleys, residential houses, old streets, courtyard layout, humanistic landform, historical texture	It mainly appears in Beijing-Flavor Culture (historical blocks) and Ancient Capital Culture (imperial city texture). As a composite dimension of "architectural aesthetics" and "natural landscape", it emphasizes the spatial pattern evolved by the interaction between human and nature.
17	Tourist Services	Service Facilities and Convenience	It refers to the public's evaluation of the quality of various services provided by cultural venues, including service procedures and quality such as guided tours, ticket management, complaint handling and security management.	Services, tour guides, explanations, staff, ticket sales, ticket checking, service attitude, complaints, management level	This dimension can be found in all four types of culture. Venues of Innovative Culture such as museums and theatres generally receive better service evaluations than traditional scenic spots. A distinction shall be made between "public facilities" (hardware) and "tourist services" (software services).

Table A2. Entropy weight method calculation results for 17 evaluation aspects.

No.	Evaluation Aspect	Actual Frequency n_i	Frequency Ratio p_i	Information Entropy e_i	Differentiation Coefficient d_i	Weight w_i	Evaluation Dimension
1	Cultural Experience	73,058	26.388%	0.1241	0.8759	0.0542	Cultural Value and Heritage
2	Culinary Experience	46,324	16.732%	0.1056	0.8944	0.0553	Service Facilities and Convenience
3	Cultural Atmosphere	33,851	12.227%	0.0907	0.9093	0.0562	Cultural Value and Heritage
4	Natural Landscape	26,388	9.531%	0.0791	0.9209	0.0570	Natural Landscape and Environment
5	Cultural Connotation	19,440	7.022%	0.0658	0.9342	0.0578	Cultural Value and Heritage
6	Commercial Environment	9942	3.591%	0.0422	0.9578	0.0592	Service Facilities and Convenience
7	Visitor flow	9377	3.387%	0.0405	0.9595	0.0593	Experience Quality and Comfort
8	Physical Exertion	9199	3.323%	0.0399	0.9601	0.0594	Experience Quality and Comfort
9	Emotional Resonance	8666	3.130%	0.0383	0.9617	0.0595	Experience Quality and Comfort
10	Architectural Aesthetics	8602	3.107%	0.0381	0.9619	0.0595	Cultural Value and Heritage
11	Historical Cognition	6190	2.236%	0.0300	0.9700	0.0600	Cultural Value and Heritage
12	Weather and Climate	5621	2.030%	0.0279	0.9721	0.0601	Experience Quality and Comfort
13	Public Facilities	4385	1.584%	0.0232	0.9768	0.0604	Service Facilities and Convenience
14	Cultural Heritage	4052	1.464%	0.0218	0.9782	0.0605	Cultural Value and Heritage
15	Transportation Convenience	4033	1.457%	0.0217	0.9783	0.0605	Service Facilities and Convenience
16	Human Landscape	3958	1.430%	0.0214	0.9786	0.0605	Natural Landscape and Environment
17	Tourist Services	3775	1.364%	0.0207	0.9793	0.0606	Service Facilities and Convenience
total		276,861	100.000%			1.0000	

Table A3. Hyperparameter configuration for non-negative CP tensor decomposition.

Parameter Category	Parameter Value	Description
Tensor Dimensions	$4 \times 17 \times 3 \times 5$	Fourth-order tensor: Cultural Category (four) $\times$ Evaluation Aspect (17) $\times$ Sentiment Polarity (three) $\times$ Spatial Carrier Type (five)
Decomposition Method	Non-negative CP decomposition (NN-CP)	Non-negativity constraints are implemented via Multiplicative Update Rules (MUR), ensuring all elements in factor matrices are ≥ 0 and enhancing result interpretability.

Table A3. *Cont.*

Parameter Category	Parameter Value	Description
Rank R for Decomposition	Rank R = 9	The rank is determined using the Elbow Method: the reconstruction error decreases significantly when R increases from eight to nine, while the reduction rate plateaus when $R \geq 10$. At R = 9, the model achieves an explained variance of 94.87% with optimal robustness.
Initialization Strategy	Random non-negative initialization (50 trials)	Factor matrices are initialized with 50 random non-negative initializations, and the initialization with the minimum reconstruction error is selected as the final optimization starting point to effectively avoid local optima.
Convergence Criterion	Relative residual decrease $< 1 \times 10^{-6}$	Convergence is determined when the relative decrease in reconstruction error between two consecutive iterations is less than 1×10^{-6} ; a maximum iteration limit of 500 is set to prevent overfitting.
Regularization Method	L2 regularization ($\lambda = 0.001$)	L2 regularization is applied to factor matrices to constrain excessive coefficients, with the regularization strength ($\lambda = 0.001$) determined via five-fold cross-validation.
Numerical Stability Processing	Small offset ($\varepsilon = 1 \times 10^{-10}$)	A small positive value $\varepsilon = 1 \times 10^{-10}$ is added to the denominator during multiplicative updates to prevent numerical instability caused by division by zero.
Sparsity Processing	Zero-filling strategy	Missing values in the tensor (cells with zero frequency for partial cultural category–aspect–polarity–carrier combinations) are filled with zeros instead of mean imputation to preserve sparse structural information.
Implementation Tool	Python 3.10 + tensorly 0.8.1	The implementation relies on the open-source tensor decomposition library TensorLy. A single complete decomposition takes approximately 3.2 min on a high-performance computing server.

Table A4. Methodological comparison: CP decomposition vs. LDA vs. NMF.

Comparison Dimension	CP Decomposition (This Study)	LDA Topic Model	NMF Non-Negative Matrix Factorization
Comparison Dimension	It natively supports N-order tensors (4th-order in this study) and models multi-dimensional interactions without dimension reduction.	It only supports two-dimensional document-term matrices. The data of this study has to be flattened into such matrices, which leads to the loss of information about cultural categories and spatial carriers.	It only supports two-dimensional non-negative matrices. Similar to LDA, it requires information compression for high-order data.
Data Structure Adaptation	It fully retains the four-dimensional interactive structure: four cultural categories $\times$ 17 evaluation aspects $\times$ three sentiment polarities $\times$ five carriers. Each latent pattern corresponds to an interpretable four-dimensional joint distribution.	It generates two matrices: document-topic distribution and topic-word distribution, and cannot distinguish the independent contributions of sentiment polarity and spatial carriers.	It produces a basis matrix (W) and a coefficient matrix (H), which can only partially approximate high-order structures and thus have limited semantic interpretability.

Table A4. Cont.

Comparison Dimension	CP Decomposition (This Study)	LDA Topic Model	NMF Non-Negative Matrix Factorization
Dimension Fidelity	Equipped with native non-negativity constraint (NN-CP), all elements of factor vectors are non-negative. The results carry clear physical implications and can be interpreted as the intensity of cultural perception patterns.	The Dirichlet prior implicitly ensures non-negative distributions, yet it cannot guarantee the full additivity of factors.	It adopts native non-negativity constraints. The basis matrix can be interpreted as “components”, yet its additive interpretability degrades when handling data with more than four dimensions.
Non-negativity Constrain	Sentiment polarity is treated as an independent tensor dimension for joint decomposition, which directly generates coupled patterns of “specific cultural category—evaluation aspect—sentiment polarity”.	Standard LDA fails to identify sentiment polarity. Additional sentiment analysis modules such as the JST model are required, which increases the methodological complexity.	NMF can incorporate polarity information indirectly via feature expansion, but it cannot directly model the joint distribution of polarity and evaluation aspects during decomposition.
Spatial Carrier Modeling	Spatial carriers act as the fourth dimension in tensor decomposition, enabling the identification of perception patterns linked to specific carrier types (e.g., perception oriented to imperial heritage).	Spatial information is imported indirectly through metadata and cannot be natively modeled within the topic decomposition framework.	Data processing relies on matrix expansion, such as appending spatial labels to matrix rows, resulting in limited spatial interpretability of decomposition outputs.
Interpretability	Each rank-one component can be directly defined as a cultural perception pattern, which corresponds to specific preferences for cultural categories, combinations of evaluation aspects, sentiment tendencies and carrier types.	The topic-word probability distribution is highly interpretable, whereas multi-dimensional coupling relationships need to be inferred via post-processing.	The local features of the basis matrix are highly interpretable, but data compression undermines its performance in this multi-dimensional research context.
Computational Complexity	Its computational complexity is $O(RIJKL)$. A single decomposition takes about 3.2 min with GPU acceleration based on the dataset of this study.	It has a computational complexity of $O(TVK)$. Despite fast convergence, it cannot model multi-dimensional structures.	It has a computational complexity of $O(IJK)$ and achieves high efficiency, but is restricted to two-dimensional structures.
Basis for Method Selection	Given the need to preserve the integrity of the fourth-order data structure and jointly model sentiment polarity as well as spatial carriers in this research, CP decomposition presents unique methodological advantages.	It is applicable to topic detection for large-scale unlabeled texts, but not for scenarios with a standardized evaluation aspect system and the demand for multi-dimensional joint modeling.	It is suitable for local feature extraction from two-dimensional feature matrices, rather than multi-dimensional semantic coupling analysis.

Table A5. Complete ABSA aspect-level sentiment analysis validation results.

Evaluation Aspect	Sample Size	Accuracy	Precision	Recall	F1-Score	Cohen’s κ	Quality Grade
Cultural Experience	435	0.8736	0.6974	0.8851	0.7616	0.6385	Good (0.60–0.80)
Culinary Experience	312	0.8718	0.7660	0.8619	0.8046	0.7239	Good (0.60–0.80)
Cultural Atmosphere	274	0.8796	0.7092	0.8891	0.7612	0.6564	Good (0.60–0.80)

Table A5. Cont.

Evaluation Aspect	Sample Size	Accuracy	Precision	Recall	F1-Score	Cohen's κ	Quality Grade
Natural Landscape	250	0.8680	0.7396	0.8425	0.7797	0.6872	Good (0.60–0.80)
Cultural Connotation	173	0.8497	0.6728	0.8779	0.7218	0.6259	Good (0.60–0.80)
Commercial Environment	71	0.8028	0.7881	0.8005	0.7929	0.6942	Good (0.60–0.80)
Visitor Flow	67	0.7910	0.7856	0.7978	0.7912	0.6695	Good (0.60–0.80)
Physical Exertion	66	0.9091	0.8873	0.9346	0.9080	0.8388	Excellent (>0.80)
Emotional Resonance	62	0.8387	0.6896	0.8014	0.7323	0.6187	Good (0.60–0.80)
Architectural Aesthetics	62	0.8710	0.6597	0.9012	0.7377	0.5811	Fair (0.40–0.60)
Historical Cognition	44	0.8182	0.7417	0.7940	0.7515	0.6771	Good (0.60–0.80)
Weather and Climate	40	0.8000	0.6417	0.8395	0.6383	0.6126	Good (0.60–0.80)
Public Facilities	31	0.9355	0.9407	0.9407	0.9407	0.8977	Excellent (>0.80)
Cultural Heritage	29	0.7241	0.8004	0.6549	0.6993	0.4727	Fair (0.40–0.60)
Transportation Convenience	29	0.8966	0.8704	0.9412	0.8958	0.8294	Excellent (>0.80)
Human Landscape	28	0.7857	0.5529	0.5079	0.5287	0.5294	Fair (0.40–0.60)
Tourist Services	27	0.9259	0.9148	0.9148	0.9074	0.8521	Excellent (>0.80)
Total/Weighted Mean	2000	0.8495	0.7563	0.8344	0.7737	0.6827	Weighted Mean

Appendix C. Marginal Frequency Dissolution and Stability Analysis Results

This appendix presents the complete numerical results of the marginal frequency dissolution experiment and CP decomposition stability analysis described in Section 4.3. Specifically, it includes: (1) variance decomposition of the observed fourth-order count tensor into marginal frequency and multi-way interaction components, along with associated statistical tests (Table A6); (2) CP decomposition stability statistics across 50 random initializations, including pairwise Factor Match Scores (FMSs) between original and residual decompositions (Table A7); and (3) rank sensitivity analysis across $R = 3, 5, 7, 9, 11, 13$, and 15 for both the original and residual tensors (Table A8). These results collectively substantiate that the nine latent cultural perception patterns extracted by CP decomposition at $R = 9$ (Table A9) represent genuine higher-order interaction structures rather than artifacts of marginal frequency distributions.

Table A6. Marginal frequency variance decomposition results.

Component	Description	Sum of Squares	Proportion
Marginal Frequencies (Independence Model)	Variance explained by the outer product of four marginal probability distributions: $T_{indep} = p_{cultural} \otimes p_{aspect} \otimes p_{polarity} \otimes p_{spatial} \times N$	714,284,453.05	65.5%
Multi-way Interaction Residual	Variance arising exclusively from higher-order interactions among cultural type, evaluation aspect, sentiment polarity, and spatial carrier: $T_{resid} = T_{observed} - T_{indep}$	376,512,737.95	34.5%
Total	Total sum of squares of the observed fourth-order count tensor ($4 \times 17 \times 3 \times 5 = 1020$ cells)	1,090,797,191.00	100.0%

Table A7. Supplementary goodness-of-fit and association statistics.

Statistic	Value	Interpretation
Total observations (N)	276,821	Number of valid geotagged social media posts
Tensor dimensions	$4 \times 17 \times 3 \times 5$	Cultural Type $\times$ Evaluation Aspect $\times$ Sentiment Polarity $\times$ Spatial Carrier
Non-zero cell proportion	99.6%	1016 of 1020 cells are non-zero
Independence model fit	41.25%	Frobenius-norm fit of T_{indep} to $T_{observed}$
Pearson χ^2	386,326	df = 994, $p < 0.001$
Likelihood-ratio G^2	211,872	df = 994, $p < 0.001$
Cramér's V	0.8353	Large effect size ($V > 0.50$)

Table A8. CP decomposition stability statistics and factor matching results (50 random initializations, R = 9). (a) Stability statistics across 50 random initializations. (b) Factor Match Scores between original and residual CP factors (optimal Hungarian matching).

(a)			
Metric	Original Tensor		Residual Tensor
Best Fit (%)	95.73		93.04
Mean Fit (%)	93.21		92.66
Std (%)	1.90		0.31
Coefficient of Variation (%)	2.04		0.33
Stability FMS (mean ± std)	0.666 ± 0.092		0.706 ± 0.084
(b)			
Original CP Factor	Matched Residual CP Factor	FMS	Corresponding Pattern
Factor 1	Factor 9	0.985	Pattern 1: Beijing-Flavor Culinary Identification
Factor 2	Factor 6	0.081	
Factor 3	Factor 2	0.905	Pattern 3: Performance–Commercial Overload
Factor 4	Factor 5	0.274	
Factor 5	Factor 1	0.631	—
Factor 6	Factor 8	0.790	—
Factor 7	Factor 4	0.498	—
Factor 8	Factor 3	0.987	Pattern 8: Historical–Cultural Root-Seeking
Factor 9	Factor 7	0.283	
Mean FMS	—	0.604	—

Note: The residual tensor is obtained by subtracting the independence model from the observed tensor, thereby removing all marginal frequency effects. CP decomposition on this residual tensor achieves a fit of $93.04\% \pm 0.31\%$,

closely comparable to $95.73\% \pm 1.90\%$ for the original tensor. The average FMS of 0.604 between original and residual CP factors indicates moderate structural consistency, with three factor pairs exceeding 0.90 (Factor 1 $\leftrightarrow$ Factor 9: FMS = 0.985; Factor 3 $\leftrightarrow$ Factor 2: FMS = 0.905; Factor 8 $\leftrightarrow$ Factor 3: FMS = 0.987), confirming that these key latent patterns—Beijing-Flavor Culinary Identification, Performance–Commercial Overload, and Historical–Cultural Root-Seeking—are anchored in genuine multi-way interaction structures rather than marginal artifacts. The remaining factors undergo structural reorganization after marginal effects are partialled out, demonstrating that CP decomposition captures information beyond simple marginal re-expression. The stability FMS values (0.666 for original; 0.706 for residual) across 50 random initializations confirm that the decomposition results are robust and not sensitive to initialization choices.

Table A9. Rank sensitivity analysis results (R = 3, 5, 7, 9, 11, 13, 15).

Rank R	Original Tensor Fit (%)	Residual Tensor Fit (%)	Δ Fit (Orig. – Resid.)	Incremental Gain (Original)
3	80.26	66.12	14.14	—
5	82.47	78.70	3.77	+2.21
7	91.71	84.88	6.83	+9.24
9	94.32	91.02	3.30	+2.61
11	96.39	94.95	1.44	+2.07
13	96.30	95.38	0.92	−0.09
15	95.19	96.43	−1.24	−1.11

Note: “—” denotes not applicable. R = 9 is identified as the elbow point using the Elbow Method. The original tensor fit increases substantially from R = 7 (91.71%) to R = 9 (94.32%), representing a 2.61-percentage-point gain, while further increases in R yield diminishing returns: R = 11 (96.39%, +2.07 pp), R = 13 (96.30%, −0.09 pp), and R = 15 (95.19%, −1.11 pp), the latter two indicating overfitting where the fit actually decreases. The residual tensor exhibits a similar elbow pattern at R = 9 (91.02%), with the fit continuing to increase for higher ranks but at a rapidly decelerating rate. The negative Δ Fit at R = 15 (−1.24 pp) indicates that the residual tensor achieves a higher fit than the original tensor at this rank, suggesting over-decomposition where noise components are being modeled. Collectively, these results confirm that R = 9 provides the optimal balance between model complexity and explanatory power for both the original and residual tensors.

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