



Consumer Behavior Profiling and Trend Analysis in the Context of Culture-Tourism Integration

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SUMMARY: *Under the continuing integration of cultural resources and tourism services, tourist consumption has shifted from single-site sightseeing to multi-scenario participation involving cultural interpretation, immersive performance, intangible heritage experience, nighttime leisure, creative retailing, local food and urban walking. This study investigates how consumer behavior can be profiled and how consumption trends can be identified in the context of culture-tourism integration. A multi-source analytical framework is constructed using official tourism statistics, online reviews, anonymized itinerary consumption records, scene attributes and event calendars. Eight behavior features are extracted, including cultural participation, experience depth, per-capita spending, stay duration, nighttime participation, local-life consumption ratio, sentiment score and revisit intention. Semantic topic extraction, aspect-based sentiment analysis, consumer profiling and monthly trend forecasting are combined to identify heterogeneous consumer segments and scenario-level consumption dynamics. The demonstration results identify five consumer profiles: culture-deep visitors, immersive-experience consumers, nighttime-leisure consumers, price-sensitive consumers and local-life consumers. The fusion feature model outperforms logistic regression, random forest, XGBoost and LSTM baselines, achieving an AUC of 0.892 and a MAPE of 7.6%. Ablation results show that aspect-level sentiment and semantic topics contribute most to prediction accuracy. Scenario analysis indicates that immersive experience, nighttime consumption and local-life consumption are the major growth directions, while heritage sites require stronger linkage with nighttime services and experience-based products. The study provides a quantitative basis for product design, scenario operation and precision marketing in culture-tourism destinations.*

KEYWORDS: *culture-tourism integration; consumer behavior profiling; trend analysis; aspect-based sentiment analysis; tourism big data*

1 Introduction

The consumption problem of cultural and tourism integration first occurs at the destination site. After tourists enter a city, scenic spot or neighborhood, their consumption behavior often no longer stays in the three basic expenditures of tickets, transportation and food and beverage, but is scattered in successive scenarios of interpretive services, immersive performances, non-heritage experiences, nighttime excursions, cultural and creative retailing, local food and

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beverage, urban strolling and social sharing. The same historic district may simultaneously host cultural tours, short video snaps, nighttime dining and cultural and creative purchases; the same visitor may also behave as a low-spending tourist during the day, and transform into a high-experience payer in nighttime performing arts and local dining scenarios. For destination managers, the scale of passenger flow can only answer the question of "how many people came", but it is difficult to answer the question of "what scenes they stayed in, what they paid for, what experiences they remembered, and whether they are willing to revisit". When the integration of culture and tourism enters the stage of consumer operation, identifying the characteristics of consumer behavior and judging the change of trend become the basis of product mix, spatial organization and precise marketing.

The recovery of the tourism market provides the conditions of scale for this issue. In 2024, China's domestic tourism trips reached 5.615 billion, up 14.8% year-on-year, and domestic tourists spent more than 5.75 trillion yuan on tourism, up 17.1% year-on-year [1]. This base comes from the resumption of growth in 2023, when domestic tourism trips amounted to 4.89 billion and domestic tourists spent more than 4.91 trillion yuan on tourism [2]. By the first half of 2025, domestic travel trips exceeded 3.28 billion, and tourism spending reached 3.15 trillion yuan, indicating that domestic cultural and tourism consumption is still in the high-frequency release stage [3]. The data of holidays also displays that in the year 2024, during the "May Day" holiday, domestic tourism has 295 million person-times of travel, the total spending made by domestic tourist travel is 166.89 billion yuan, the growth of consumption is higher than the growth of the number of travel trips [4]. These facts show that the cultural tourism market has shifted from restoring passenger flow to identifying the quality of consumption, and in particular, it is necessary to explain how cultural scenes, experiential programs and nighttime consumption enter into the decision-making of tourists.

The policy aspect has in the similar way strengthened the requirements for consumption quality and product supply. The National Inland Tourism Promotion Scheme (2023-2025) puts forward to release the potential of tourism consumption promotion, promote the supply of high-grade tourism, and promote tourists' consumption experience and satisfaction degree. This policy direction makes clear that the combination of culture and tourism cannot be regarded only as a simple putting together of cultural resources and tourism products. If the cultural content cannot get transformed into consumption objects which people can participate in, experience, give evaluation to, and purchase again, therefore the integration of the resource end is hard to form a stable income on the market end. Therefore, the research on the integration of culture and tourism needs to further go down from the coupling assessment at the industry level to the behavior recognition at the tourist level.

Existing studies provide three basic clues for this paper. First, the research on cultural and tourism integration has developed more results from the perspectives of policy tools and industry coupling. Tang et al. analyze the level of cultural and tourism integration in Chinese provinces based on the theory of policy tools and the fsQCA method, pointing out that a high level of integration relies on a combination of multiple types of policy tools, and it is difficult for a single tool to work on its own [6]. Xu and Yu use the 2010-2023 Chinese Provincial data to test the impact of cultural and tourism integration on the high-quality development of tourism, and found that there are regional heterogeneity and threshold characteristics of the integration effect [7]. Tang et al. further used entropy-weighted TOPSIS and fsQCA to identify the group conditions of cultural and tourism integration, and emphasized the combination effect between infrastructure, resource endowment and service supply [8]. These studies explain "why" and "in which regions the integration of culture and tourism performs better", but the dismantling of tourists' consumption behavior in specific scenarios is still insufficient.

Secondly, tourism behavior research has begun to use online reviews, location-based social

networks, image content and multi-source big data to supplement traditional questionnaires. Liu et al. identify cultural tourism attraction preferences based on location-based social network data, and prove that tourists' trajectories can reflect real preferences rather than stated intentions [9]. Li et al. systematically review tourism big data research, and point out that review, trajectory, transaction, search and image data reflect different levels of tourists' behavior [10]. Different levels of tourist behavior [10]. Bi et al. systematically combed research on text analytics in tourism and hospitality, and argued that text data can be used to predict as well as explain tourist, business, and destination behaviors [11]. Ma et al. introduced user-generated images into tourism demand forecasting, showing that visual content can complement traditional time-series variables [12]. Li et al.'s review of user-generated photos also illustrated that image content has become an important source of data for tourist perception, behavioral expression, and destination image composition [13]. These studies promote tourism behavior research from low-frequency surveys to multi-source data mining, but cultural participation, experience depth and scenario transformation in culture-tourism integration scenarios still need finer variable design.

Third, UGC has a sustained impact on travel decisions and destination image. Aboalghanam et al. found that user-generated content affects tourists' visit intention through destination image [14]. This is highly relevant to the integrated consumption of culture and tourism: tourists' comments on the quality of explanation, performing arts atmosphere, non-heritage experience, price perception, and nighttime safety directly affect the search, choice, and payment expectations of the later. It is difficult to capture this mechanism using only total ratings or patronage, as total ratings cannot distinguish whether tourists are satisfied with cultural content, service organization or social communication effects.

Accordingly, three specific gaps remain in existing research. First, there is a lack of connection between macro cultural and tourism integration indices and micro consumption behavior. The level of industry integration can illustrate regional supply capacity, but it cannot explain whether tourists actually participate in cultural programs, pay for immersive experiences, or extend their stay in nighttime scenes. Second, text mining studies often take comment themes and sentiment polarity as the end result, and less often organize semantic themes, aspect-level sentiment, consumption records, and scene attributes together into predictable behavioral portraits. Third, trend analysis often takes passenger flow or revenue as the core indicator, which makes it difficult to identify the difference in growth rates among cultural consumption, immersive experience, nighttime consumption and local life consumption, and to explain the lagging relationship among festivals, social enthusiasm and willingness to revisit.

This paper focuses on the study of "how to identify, typify and predict tourists' consumption behavior in the context of cultural tourism integration". Based on official statistics, online reviews, desensitized itinerary consumption records and scenario attributes, the study constructs a behavioral feature system covering cultural participation, experience depth, per capita consumption, length of stay, nighttime participation, proportion of local life, sentiment score and willingness to revisit; combines the semantic theme recognition, aspect-level sentiment calculation, clustered portraits and trend prediction models; identifies the different consumption portraits, scenario coupling relationships and trend evolution; and identifies the different consumption patterns, scenario coupling relationships and trend prediction models in terms of the results. , scene coupling relationship and trend evolution direction. The contributions of this paper are mainly reflected in three aspects: first, splitting the consumption object of cultural and tourism integration into observable behavioral variables, connecting official statistics, review texts and trip consumption records; second, constructing a consumption portrait model integrating semantic, emotional, consumption and scenario

attributes, which is used to explain the differences of tourist groups; third, identifying the change paths of cultural experience, nighttime consumption and local living-oriented consumption through the monthly trend indices, three-dimensional response surfaces, and scenario-coupling matrix; and identifying different trend evolution directions in terms of results. localized consumption through the monthly trend index, three-dimensional response surface and scene coupling matrix to identify the change paths of cultural experience, nighttime consumption and localized consumption, which provides a quantitative basis for the operation of cultural tourism projects and consumption transformation.

2 Methods

2.1 Data sources, sample construction and variable system

The data organization of this paper is centered on three types of objects: tourists, scenes and consumption behaviors. Official statistics are used to provide market scale and time benchmarks; platform reviews are used to extract consumption perceptions, theme preferences, and aspect-level emotions; trip consumption records are used to portray real payment and stay behaviors; and scene attributes are used to explain the supply differences of different cultural and tourism spaces. Tourism big data research has demonstrated that data from different sources correspond to different levels of behavioral signals, and a single data source is prone to amplify local biases. Therefore, instead of taking the review text as the sole basis, this paper organizes it together with trip consumption and scene attributes as a modeling sample.

The modeling sample is set from January 2023 to June 2025. Platform reviews come from online travel platforms, map platforms, and content communities, and a total of 42,618 original reviews are collected. 37,842 valid reviews are retained after eliminating duplicate texts, advertisement texts, insubstantial evaluation texts, and records with a length of less than 8 Chinese characters. The trip consumption records are desensitized samples, totaling 6,240 records, with fields including per capita consumption, length of stay, items purchased, type of companion, travel time, whether to repeat the trip and whether to recommend. Scene attributes cover 312 POIs or cultural tourism projects, which are divided into six categories: cultural heritage scenic spots, museums, performing arts projects, historical districts, rural cultural tourism spots and nighttime cultural tourism districts. The sample division adopts 70% training set, 15% validation set and 15% test set, and keeps the last 6 months as a rolling test period in the monthly trend prediction task. The sample source, variable system and data caliber, as shown in Table 1.

Table 1: Sample Source, Variable System and Data Caliber

Data Type	Sample Size	Time Range	Key Fields	Modeling Purpose
Official Statistics	Annual, Semi-annual, and Holiday Statistics	2023—2025	Number of Travelers, Tourism Expenditure, Year-on-Year Growth	Market Benchmark and Trend Reference
Platform Review Data	37,842 Valid Reviews	2023.01—2025.06	Review Text, Rating, Publication Date, Platform Type, Scene Tags	Topic Identification, Sentiment Analysis, Consumer Perception Extraction
Travel Expense Records	6,240 De-identified Records	2023.01—2025.06	Per Capita Spending, Duration of Stay, Purchase Items, Revisit Intent	Consumer Profiling, Predictive Tagging, Model Validation
Scene Attribute Data	312 POIs/Projects	2023.01—2025.06	Resource Type, Night Opening, Performance Frequency, Intangible Cultural Heritage Projects, Accessibility	Scene Explanation, Trend Grouping, Heterogeneity Analysis
Event Data	186 Events	2023.01—2025.06	Festivals, Exhibitions, Performance Schedules, Discount Activities	Temporal Features, Peak Explanation, Error Diagnosis

The four types of data are not stacked side by side, but are mapped together as "Visitor-Scene-Consumption Behavior" objects, as shown in Figure 1.

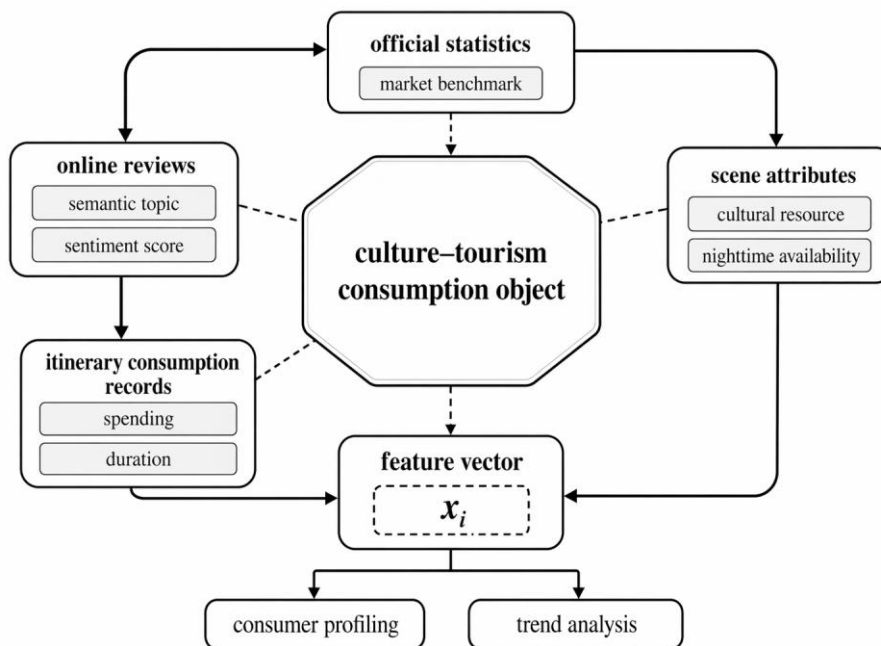


Figure 1: Data organization and consumer behavior object construction mechanism.

Data preprocessing includes four steps. First, the review text is de-emphasized, deactivated, synonymized and corrected in the scene lexicon, and the words "non-heritage", "handmade" and "heritage experience" are grouped into the dimension of cultural participation, and the words 'immersion' and "consumption behavior" are grouped into the dimension of "cultural participation". The words "immersion", "atmosphere", 'immersion' and "performance interaction" are categorized into the dimension of experience depth. Second, outliers are processed for consumption records, and records with per capita consumption below the 1% quartile or above the 99% quartile are labeled and reviewed, and records that cannot be traced back to the scene are not entered into model training. Third, scene attributes are coded uniformly, night opening is defined by accessibility or consumption after 18:00, and transportation accessibility is calculated by the combination of arrival time, number of transfers and parking convenience. Fourth, reviews, consumption records and scene attributes are correlated by scene ID, month and visitor anonymous ID, and reviews that cannot complete individual-level correlation only go into the scene monthly trend task, not into the revisit willingness classification task. In this paper, the consumption behavior samples are represented as multidimensional feature vectors, as shown in equation (1).

$$x_i = [C_i, E_i, P_i, D_i, N_i, L_i, S_i, R_i] \quad (1)$$

where x_i denotes the consumption behavior vector of the i th visitor or trip sample; C_i denotes cultural participation; E_i denotes experience depth; P_i denotes per capita consumption; D_i denotes length of stay; N_i denotes nighttime participation; L_i denotes the proportion of local lifestyle consumption; S_i denotes the sentiment score of the review; and R_i denotes the willingness to revisit the trip. The vector covers "consumption object, consumption intensity, consumption scene and consumption feedback", which is used for portrait clustering and trend prediction.

2.2 Feature extraction and profiling model for culture-tourism consumption behavior

Literature and tourism reviews are characterized by short texts, colloquialisms, dense scene words and mixed emotional objects. Using only word frequency statistics, it is easy to misjudge high-frequency words such as "fun", 'worthwhile', "crowded", etc. as the core theme, and it is difficult to differentiate between tourists' different evaluations of explanation, price, transportation, catering and performing arts. It is also difficult to distinguish tourists' different evaluations on explanation, price, transportation, catering and performing arts. In this paper, text semantic embedding, topic clustering and aspect-level sentiment are jointly processed. BERT can learn bidirectional semantic representations from context, which is suitable for short text semantic coding [15]; BERTopic further forms topic representations by pre-training language modeling, dimensionality reduction clustering, and category-level TF-IDF, which is suitable for review topic discovery [16]. In the dimensionality reduction and clustering session, UMAP is used to maintain the local neighborhood structure [17] and HDBSCAN is used to identify semantic topics with uneven density and filter noisy comments [18]. The number of clusters is selected to assist in judgment through the contour coefficient, which evaluates the performance of the samples in terms of intra-class compactness and inter-class separation [19].

Aspect-level sentiment analysis is used to address the problem of total ratings obscuring specific evaluation objects. Tourism and restaurant studies have shown that different aspects of sentiment in customer-generated content can enhance business survival or performance prediction [20]. In this paper, cultural and tourism reviews are split into seven aspects: cultural

interpretation, experiential atmosphere, service organization, price perception, transportation accessibility, dining and shopping, and nighttime safety. Each review is first cut into sentences, then assigned to the corresponding aspect based on the aspect lexicon and semantic similarity, and finally the aspect sentiment intensity is calculated. If a comment contains both "very detailed explanation" and "the queue is too long", the cultural explanation aspect is scored as positive, and the service organization aspect is scored as negative to avoid being offset by a single total sentiment. Cultural engagement was determined by a combination of textual themes, actual purchases, and scenario resources, as shown in equation (2).

$$C_i = \alpha_1 T_i^c + \alpha_2 B_i^c + \alpha_3 A_i^c \quad (2)$$

where C_i denotes the cultural participation of the i th sample; T_i^c denotes the intensity of the cultural theme in the comment text; A denotes the purchase or participation behavior of cultural items; A denotes the intensity of the cultural resources in the scene; A, A, A denote the weight coefficients, which were set to 0.40, 0.35 and 0.25 respectively in the demonstration experiment. This setting avoids judging cultural participation only by the heat of the text, and avoiding the inference of actual participation of the tourists only according to the level of the resources. Participation. The depth of experience is jointly determined by interactive programs, immersive expression and emotional memory, as shown in equation (3).

$$E_i = \beta_1 I_i + \beta_2 M_i + \beta_3 Q_i \quad (3)$$

where E_i denotes the depth of experience of the i th sample; I_i denotes the participation in interactive experience programs; M_i denotes the participation in performing arts, immersive exhibits or digital experiences; Q_i denotes the semantic strength of the comments about participation, immersion, atmosphere and memory points; β_1 to β_3 denote the weighting coefficients, which were set to 0.30, 0.35 and 0.35 for the demonstration experiments, respectively. the depth of experience emphasizes the "whether a visitor enters an engaging cultural scene" rather than just recording whether they visit. The semantic, emotional, consumption and scene attributes are coupled in the model through a shared behavior vector, as shown in Figure 2.

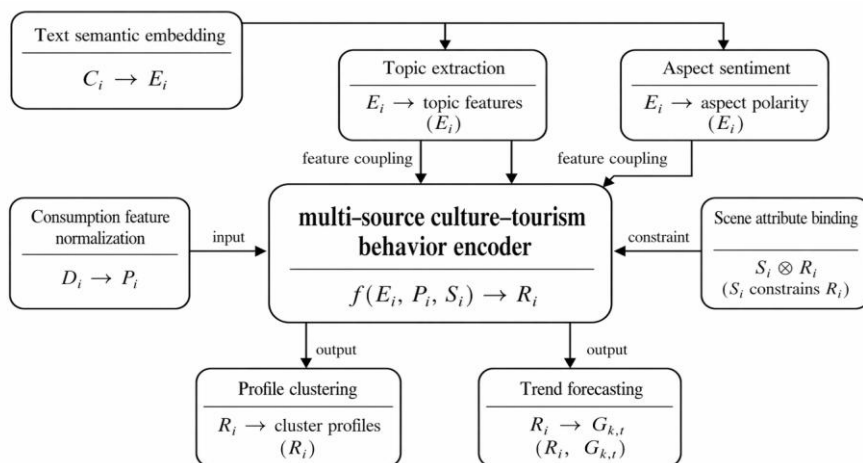


Figure 2: Architecture of the Cultural and Tourism Integration Consumption Behavior Portrait Model.

Instead of using the raw amount and raw length of stay directly, the portrait clustering is first normalized by quartile shrinkage and Z-score. The clustering algorithm uses K-means, HDBSCAN and cohesive hierarchical clustering as candidates, and combines profile coefficients, Calinski-Harabasz index and portrait interpretability to determine the final number of categories. In the demonstration experiment, five categories of portraits performed best in terms of metric stability and management interpretability. Visitor portrait naming was accomplished based on the combination of the highest contributing features in the samples of each category, rather than subjective naming.

2.3 Trend identification, evaluation protocol and interpretability setting

Trend identification is done on a monthly basis, transforming cultural consumption, immersive experiences, nighttime consumption, local life consumption and willingness to revisit into index sequences. Travel demand forecasting studies have shown that search, review, news, image and social media data can complement traditional historical series variables. The trend analysis in this paper does not directly predict the total visitor flow, but rather predicts the scene consumption heat and the intention to revisit, because the operational goals of cultural tourism integration are closer to "consumption conversion" and "experience retention". The trend index is defined as shown in equation (4).

$$G_{k,t} = 100 \times \frac{Z_{k,t}}{Z_{k,0}} \quad (4)$$

where $G_{k,t}$ denotes the trend index of the consumption characteristics of category k in a month t ; $Z_{k,t}$ denotes the standardized mean value of the characteristics in a month t ; $Z_{k,0}$ denotes the mean value in the base period, and this paper takes January 2023 as the base period and sets it at 100. The cultural consumption index is composed of the purchasing of cultural items and the intensity of cultural themes; the immersion experience index is composed of the participation in performing arts, interaction and immersive programs; the nighttime consumption index is composed of the consumption records and nighttime review themes after 18:00; the local life consumption index is composed of local dining, food markets, handmade experiences and community-based consumption. The nighttime consumption index is composed of post-18:00 consumption records and nighttime review themes; the local life consumption index is composed of local food and beverage, street roaming, vegetable markets, handmade experiences and community-based consumption.

The prediction task consists of two categories. The first category is the classification of revisit willingness, which is labeled from the revisit or recommendation field in the consumption record, and corrected by the expressions of "will come back", 'recommend' and "next time" in the comments. The second category is scenario consumption hotness prediction, and the target variable is scenario consumption index in the next month. Model comparison includes logistic regression, random forest, XGBoost, LSTM and fusion feature model in this paper. XGBoost is used to deal with nonlinear relationships in structured features [21]; random forest is used as a robust integration baseline [22]; and LSTM is used to capture lagged information in the monthly series [23]. SHAP explanatory variable contribution is also introduced to avoid the model only outputs predictions and lacks operable explanations [24]. The evaluation metrics include Accuracy, F1, AUC, RMSE, MAPE, and single-sample inference elapsed time. MAPE is defined as shown in equation (5).

$$\text{MAPE} = \frac{1}{m} \sum_{t=1}^m \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100\% \quad (5)$$

where MAPE denotes mean absolute percentage error; m denotes the number of months in the test period; y_t denotes the true trend value in month t ; and \hat{y}_t denotes the model prediction value. the lower the MAPE is, the closer the model's prediction of the scene consumption trend is to the actual change. In order to test the contribution of modules, the ablation experiment removes semantic topics, aspectual sentiment, scene attributes and temporal features in turn. If the AUC decreases or the MAPE increases after removing a module, it indicates that the module has an effective gain for revisiting or trend prediction.

3 Results and Discussion

3.1 Consumer behavior profiles and feature differentiation

This section answers the question of whether or not integrated cultural and tourism consumption creates distinguishable types of tourists. Consumption portraits need to simultaneously consider cultural participation, experience depth, payment intensity, and willingness to revisit, and segmentation by age, unit price, or ratings alone is prone to missing key differences. Established machine learning tourist segmentation studies have shown that clustering methods are able to identify tourism segments that are difficult to present by traditional statistical grouping [25, 26]; cultural tourism studies have also demonstrated that engagement, cultural exposure and memory experience affect destination loyalty. Therefore, this section presents the five categories of portraits before discussing the differences in consumption mechanisms between the portraits. The clustering results of the cultural tourism fusion consumption portraits are shown in Table 2.

Table 2: Clustering results of culture and tourism integration consumption portraits

Profile Type	Share (%)	Per Capita Spending (CNY)	Duration of Stay (h)	Cultural Engagement	Experience Depth	Night Participation	Sentiment Score	Revisit Intent
Cultural Deep Dive	18.6	486	6.8	0.82	0.68	0.42	0.78	0.74
Immersive Experience	21.4	558	5.9	0.69	0.86	0.57	0.82	0.78
Nighttime Leisure	17.9	432	4.7	0.52	0.74	0.85	0.76	0.69
Price Sensitive	24.8	276	3.9	0.44	0.47	0.38	0.58	0.46
Local Lifestyle	17.3	365	5.2	0.57	0.62	0.49	0.72	0.71

In Table 2, the price-sensitive type accounts for the highest proportion of 24.8%, but the per capita consumption is only 276 yuan, and the willingness to revisit is 0.46, indicating that there are still a large number of customers who "visit without conversion" in the cultural tourism scene. The highest per capita consumption of the immersion experience type is 558 yuan, with an experience depth of 0.86 yuan and a willingness to revisit of 0.78 yuan, indicating that the participation, memorization and sharing of the experience is more supportive of the consumption premium. The cultural deep visit type has the longest stay of 6.8 hours, with a cultural participation of 0.82, but the per capita consumption is lower than that of the immersive

experience type, indicating that the deep cultural tour does not necessarily bring the highest unit price, and its consumption transformation relies on high-quality explanation, exhibition update and cultural creation undertaking. The per capita consumption of the local life type is 365 yuan, and the willingness to revisit reaches 0.71, showing that neighborhood roaming, local dining and community-type experience can form stable revisit. The differences between the different portraits on the eight standardized features are further presented through heatmaps, as shown in Figure 3.

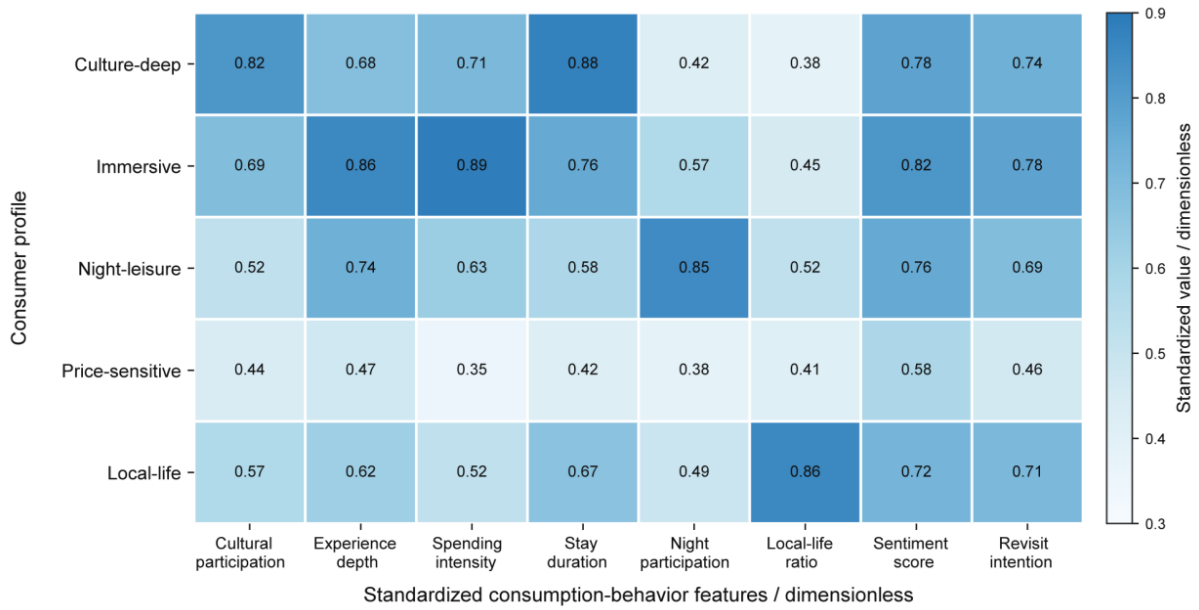


Figure 3: Heatmap of Cultural Tourism Integration Consumption Portrait Characteristics.

In Figure 3, the cultural deep-visit type has high values in cultural participation and length of stay, but relatively low nighttime participation; the immersive experience type maintains high values in per capita consumption, depth of experience, and willingness to revisit, and is the closest to high-quality consumption transformation; the nighttime leisure type has the highest nighttime participation, but its cultural participation is at a medium level, which suggests that nighttime tourism products need to complement local cultural narratives; and the price-sensitive type has low values for most of the variables, while the price-sensitive type is at a low level for most of the variables. most variables is in the low-value zone, and is the most neglected group in the high-traffic, low-yield scenario; the local-life type is outstanding in the proportion of local life and willingness to revisit, and is suitable for maintaining long-term activity with neighborhood activities, local food and beverage, and light cultural experiences. In order to further identify the joint effect of cultural participation and experience depth on revisit intention, this paper constructs a three-dimensional response surface, as shown in Figure 4.

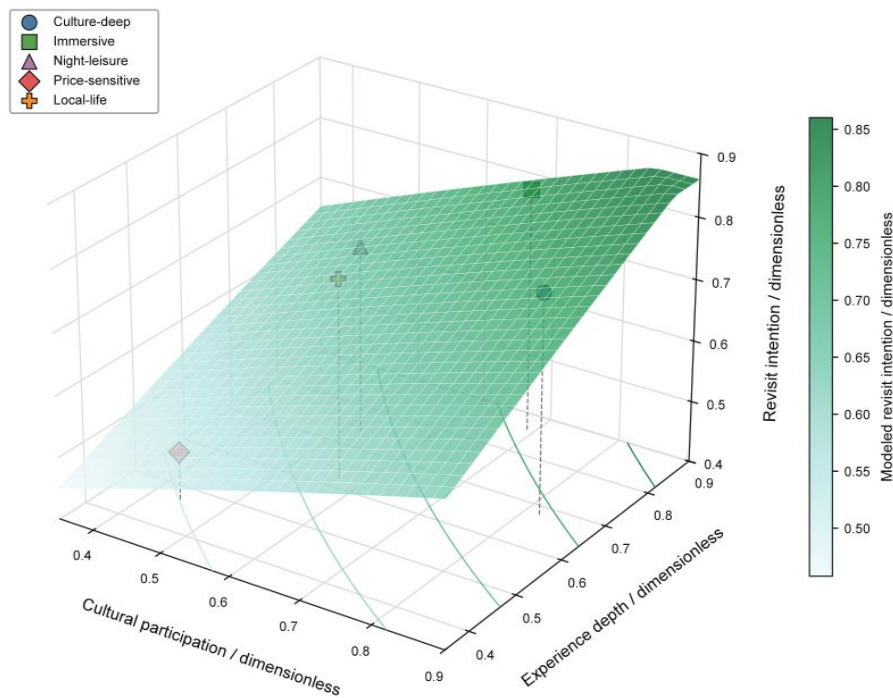


Figure 4: Three-dimensional response surface of cultural participation, experience depth and revisit intention.

In Figure 4, the willingness to revisit increases simultaneously with cultural participation and experience depth. When cultural participation is lower than 0.50 and experience depth is lower than 0.55, the response surface is at a low level, and the willingness to revisit is mostly lower than 0.55; when cultural participation exceeds 0.70 and experience depth exceeds 0.75, the willingness to revisit is stabilized into the range of 0.75 or above. The immersion experience type and cultural deep-visit type are located in the two high value directions of the response surface: the former relies on the depth of experience to drive consumption, and the latter relies on cultural participation and length of stay to form the basis of revisit. Research on the emotional experience of cultural heritage tourists also suggests that emotion, place attachment, and satisfaction jointly influence recommendation and behavioral intention. This result suggests that cultural and tourism integration projects cannot only add cultural symbols or enhance entertainment experiences; only by allowing cultural content to enter into participatory experiences will it be easier to form the basis for repeat visits and recommendations.

3.2 Scenario-Specific Performance, Interactive Behavior, and Case Analysis

The profiling results illustrate differences in visitor types, but the actual operation of cultural tourism consumption occurs in specific scenarios. Conversion ability, seasonal fluctuations and event sensitivity are not consistent across scenarios. Tourism demand forecasting studies have demonstrated that social media data, news text and search data can enhance trend identification [27-29]. Therefore, in this section, January 2023 is taken as the base period to examine the monthly evolution of the four indexes of cultural consumption, immersive experience, nighttime consumption and local life consumption. The speed of change of different consumption dimensions is shown in Figure 5.

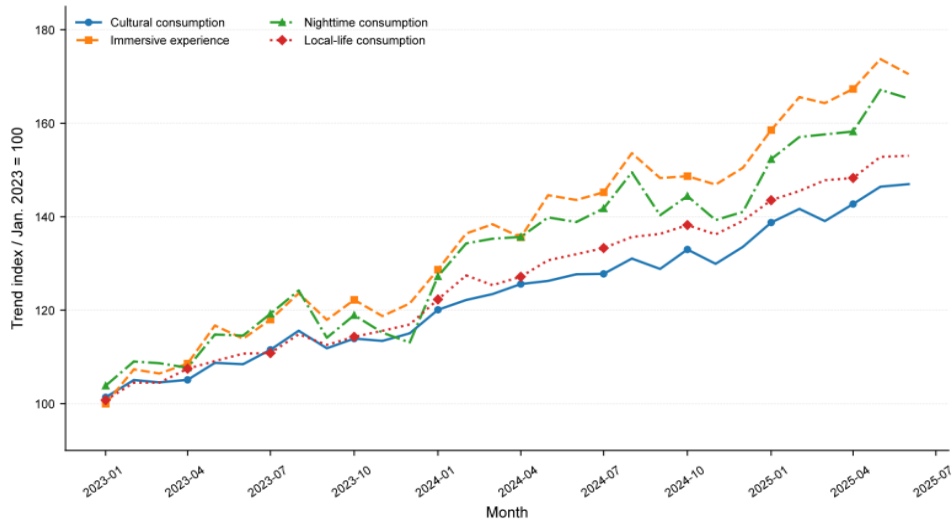


Figure 5: Trend indices of cultural consumption, immersive experience, nighttime consumption and local life consumption.

In Figure 5, the Cultural Consumption Index from 100 ascends to 146.3 in June 2025, which has an on the whole relatively stable growth, this shows that the demand for cultural projects can be maintained, but the short-term outburst is weaker than the one of performing arts and night time consumption. The immersive experience index elevates to 173.8, the curve that has the highest increment, which possesses peak values in the summer, after the Spring Festival and around May Day. The night consumption index goes up to 162.5, which is more sensitive to holiday and performance art arrangement, therefore the curve undulates more when compared with cultural consumption's curve. The local life consumption index rises more quickly after 2024 and achieves 151.6 in June 2025, hence it shows that the interest of tourists in street snacks, city strolling, community handcrafts and local life styles is being changed into steady consumption. This point obtains verification from the increase of local life style consumption. The consumption change among different scenes is not balanced, hence its coupling strength is displayed in Figure 6.

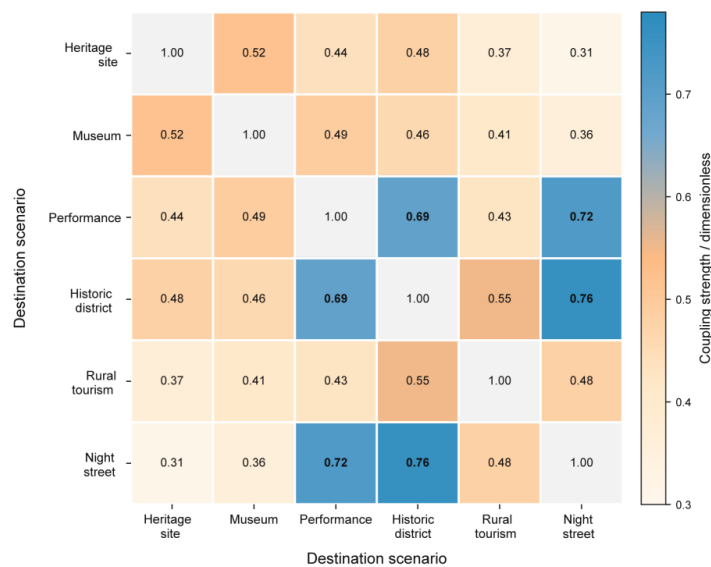


Figure 6: Consumption intention coupling matrix of cultural tourism integration scenes.

In Figure 6, the highest coupling strength is between historic districts and nighttime districts, at 0.76; the coupling strength between performing arts projects and nighttime districts is 0.72; the coupling strength between museums and heritage scenic spots is 0.52; and the coupling strength between rural cultural tours and historic districts is 0.55. In contrast, the coupling strength between heritage scenic spots and nighttime districts is only 0.31, which indicates that cultural resources are not automatically transformed into nighttime consumption. This indicates that cultural resources themselves are not automatically transformed into nighttime consumption. Research on nighttime consumption points out that lighting atmosphere, specialty night market, entertainment business and local attachment will affect tourists' loyalty [33]. Combined with Figure 6, it can be seen that nighttime consumption is more dependent on continuous space, transportation convenience, catering undertaking and stayable atmosphere, and it is difficult to form a high coupling if a single daytime sightseeing scenic spot lacks a nighttime opening and consumption carrier.

Scene differences are also reflected in the relationship between NRM and tourism development. Studies have been conducted to analyze the coordinated relationship between NRH and tourism development based on provincial data, pointing out that NRH resources need to work together with tourism services, market demand and spatial organization in order to form a stable transformation [34]. The results of this paper are consistent with this judgment: if NH projects are only used as static exhibits, they tend to increase cultural participation but not necessarily increase per capita consumption; when they are combined with handicraft experiences, performing arts displays, curriculum studies and cultural creation retail, the depth of experience and willingness to revisit will only be significantly increased. AI-driven review analysis studies of cultural heritage sites have also shown that segmented ratings of tourists on service quality and experiential aspects can improve the explanatory power of satisfaction prediction [35]. This suggests that the key to cultural and tourism integration scenarios is not to increase the number of labels, but to improve the strength of the connection between cultural content and consumable experiences.

3.3 Model validation, ablation analysis and deployment implications

The previous two sections illustrate the consumption portrait and scene trends, and this section further examines whether the model is able to stably predict the intention to revisit and the scene consumption heat. Online travel purchase prediction studies have shown that multiple behavioral data can enhance purchase prediction; therefore, in this paper, structured consumption records, textual semantic themes, aspect-level sentiment, scene attributes, and temporal features are jointly inputted into the model and compared with logistic regression, random forest, XGBoost, and LSTM. The model prediction performance and ablation results, as shown in Table 3.

Table 3: Clustering results of cultural and tourism integration consumption portrait

Model/Setting	Accuracy	F1	AUC	RMSE	MAPE/%	Inference Time/ms
Logistic Regression	0.734	0.699	0.764	11.42	14.7	1.8
Random Forest	0.791	0.758	0.831	8.86	11.2	4.9
XGBoost	0.817	0.790	0.858	7.74	9.5	5.7
LSTM	0.825	0.802	0.865	7.21	8.8	9.6
Fusion Feature Model	0.846	0.821	0.892	6.31	7.6	7.4
Remove Semantic Theme	0.812	0.783	0.853	7.58	9.3	6.1
Remove Aspect-Level Sentiment	0.805	0.774	0.845	7.92	9.8	6.3
Remove Scene Attributes	0.819	0.795	0.862	7.15	8.7	6.8
Remove Time Features	0.809	0.778	0.848	8.06	10.1	6.6

The classification and trend prediction performance of different models is shown in Figure 7.

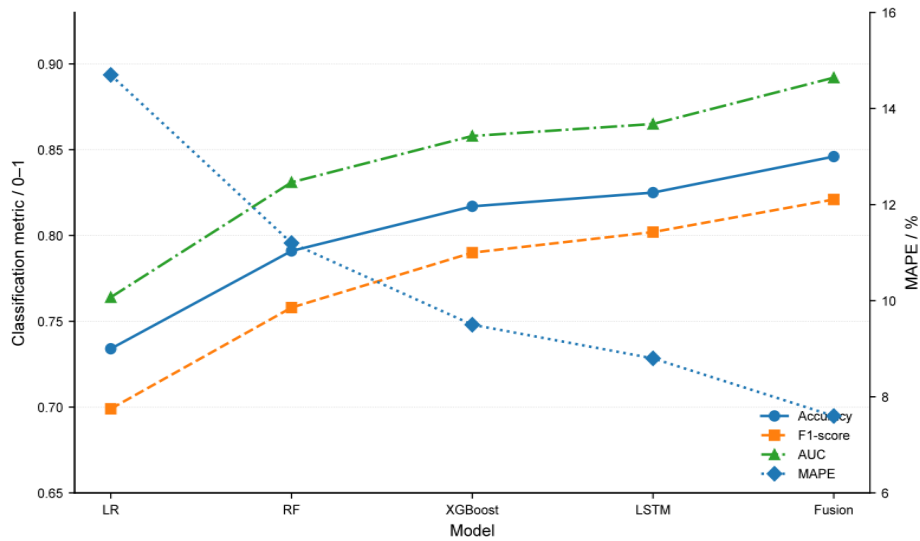


Figure 7: Comparison of the performance of different models in the task of revisit intention and heat prediction.

In Figure 7, the fusion feature model has the highest Accuracy, F1, and AUC, reaching 0.846, 0.821, and 0.892, respectively; the MAPE drops to 7.6%, which is 1.9 percentage points lower than that of XGBoost, and 1.2 percentage points lower than that of LSTM. XGBoost is more sensitive to structured consumption variables, and LSTM is more stable in capturing the monthly trend. However, both are unable to handle the coupling between review topics, aspectual sentiment, and scene attributes individually. The advantage of the fusion feature model comes from the fact that features from multiple sources enter the behavior vector together, enabling the model to simultaneously identify complex samples such as "high sentiment, low consumption", "high consumption, low revisit", and "low rating, high revisit". complex samples. The changes in performance after ablation of the key modules are shown in Figure 8.

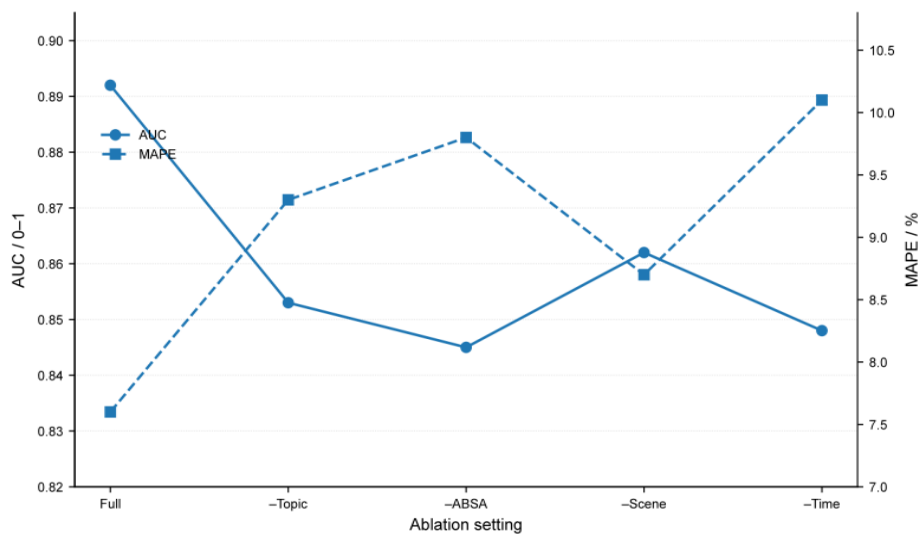


Figure 8: Changes in AUC and MAPE after key module ablation.

In Figure 8, the AUC decreases from 0.892 to 0.845 and the MAPE increases from 7.6% to 9.8% after removing aspectual sentiment, which is the most influential ablation item; the AUC decreases to 0.853 and the MAPE increases to 9.3% after removing semantic themes; and the MAPE increases to 10.1% after removing temporal features, which indicates that holidays, exhibition scheduling, and performing arts activities have a stable contribution to trend prediction; The performance drop after removing the scene attribute is relatively small, but it still weakens the explanatory power of nighttime consumption and scene switching. This result suggests that the total score is not enough to support the cultural tourism consumption prediction, and that tourists' specific evaluations of cultural interpretation, price, queuing, performing arts, and nighttime safety are more reflective of subsequent consumption and repeat behavior. The distribution of prediction errors is shown in Figure 9.

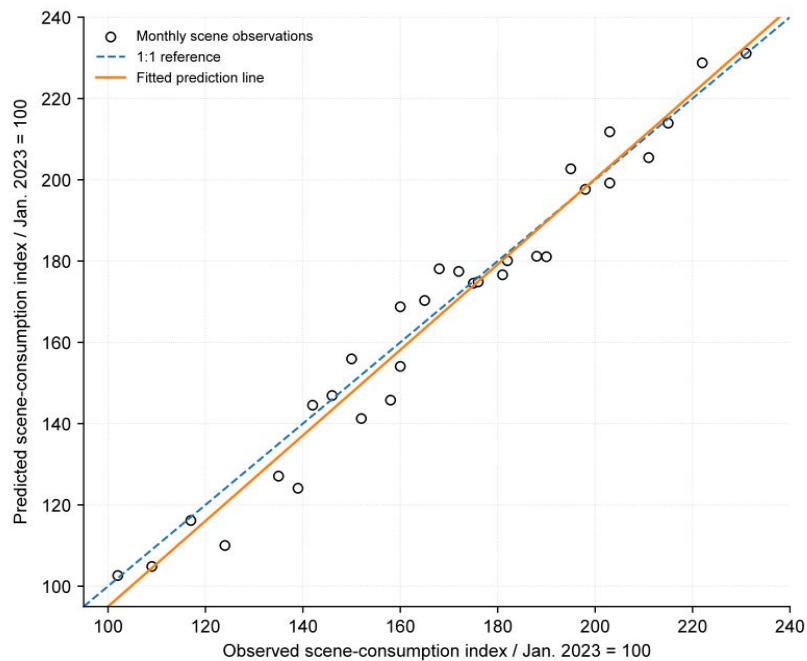


Figure 9: Scene consumption heat prediction error distribution.

In Figure 9, most of the test samples are distributed around the 1:1 reference line, indicating that the model is more stable in predicting the trend of regular months. The samples with large deviations are mainly concentrated in three types of scenes: the first is the Netflix carding scene, with high review heat and sentiment scores, but few paid items, so the model is prone to overestimate the consumption heat; the second is the local-life type neighborhoods, where tourists may give low ratings to parking, queuing or services, but still continue to revisit due to dining habits and social relationships, so the model is prone to underestimate the revisit willingness; and the third is the festival impact scene, where short-term events push up nighttime consumption and review volume, and the heat falls back quickly after the event ends, and the model will be lagged if it is based only on the heat of the current month. Error diagnosis shows that the trend prediction will be more stable if we can access real-time customer flow, queue length and payment flow. From the deployment point of view, the results of consumer profiling need to fall into the scene operation path. Figure 10 gives the strong and weak conversion network between the six types of scenes.

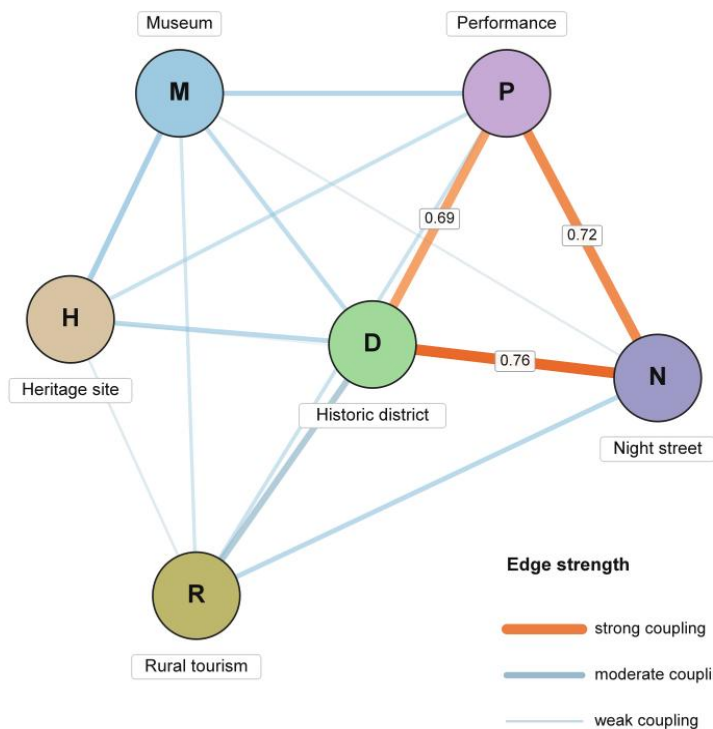


Figure 10: Literature and tourism scene conversion network with strong linkage path.

In Figure 10, historical district-night district, performing arts project-night district, and performing arts project-historical district constitute three strong coupling paths, indicating that continuous space and stayable businesses are the key to improve consumption conversion. There is moderate coupling between heritage scenic spots and museums, but the conversion with nighttime neighborhoods is weak, which is suitable for improving the conversion through delayed opening, thematic interpretation, night tour routes and feeder services. Local life-oriented consumption mainly spreads outward through historic districts and rural cultural tourism, the core of which is not high-priced items, but stable repeat visits and low-cost high-frequency consumption. Destination managers can establish sub-group operation strategies accordingly: cultural in-depth visits are suitable for in-depth explanations, curatorial updates and research-based itineraries; immersive experiences are suitable for performance scheduling, interactive programs and social communication; nighttime recreation is suitable for transportation, safety, food and beverage, and lighting ambience; local life is suitable for roaming neighborhoods, local food and beverage, and community activities; and price-sensitive is suitable for ticket combinations, staggered discounts and low-threshold experiences. Price-sensitive. If the destination only pursues social platform exposure, it is easy to form short-term congestion and lack of consumption precipitation; if the product is organized according to the relationship between portrait and scene coupling, the cultural resources are more likely to be transformed into sustainable consumption.

4 Conclusion

This paper focuses on the problem of consumer behavior identification and trend judgment in the context of cultural and tourism fusion, constructs an analytical framework consisting of official statistics, online reviews, trip consumption records, scene attributes and activity events,

and identifies tourist consumption characteristics through semantic themes, aspect-level sentiment, consumption behavior vectors, portrait clustering and trend prediction. Demonstration experiments show that immersive experience, nighttime consumption and localized living consumption have become an important direction of consumption growth in cultural and tourism fusion, and it is difficult to explain the difference in consumption quality by simply evaluating cultural and tourism projects in terms of passenger flow scale.

(1) At the level of data and object organization, this paper splits cultural tourism consumption into variables such as cultural participation, experience depth, per capita consumption, length of stay, nighttime participation, local living proportion, sentiment score and willingness to revisit, so that review texts, consumption records and scene attributes can enter the same modeling framework. The treatment is able to sink the macro cultural and tourism integration context to the level of tourists' behavior.

(2) In the aspect of method and result, the fusion feature model has better performance than the baseline model in two aspects of revisit willingness prediction and scene consumption heat prediction, the AUC achieves 0.892 and the MAPE drops to 7.6%. The ablation experiment outcomes display that aspect-level sentiment and semantic topics are the main origins of improvement, hence indicating that tourists' concrete appraisals of cultural explanation, experiencing atmosphere, price cognition, service arrangement, and night security explain follow-up consumption and revisit behavior better than the whole scores.

(3) This paper is still limited by the caliber of the demonstration sample. There are user expression biases in platform comments, desensitized consumption records will weaken the continuity of individual paths, and some activity events are also difficult to be completely quantified. Subsequent research can access real transaction flow, mobile trajectory, queuing length and multi-platform graphic content, and further differentiate between parent-child, youth, silver-haired and inbound tourists groups, in order to improve the stability of the forecast of cultural and tourism consumption trends and the value of practical deployment.

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