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Interpretable Machine Learning for Consumer Purchase Intention in Intangible Cultural Heritage: A Case Study of Nanjing Yunjin

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ABSTRACT

As a national intangible cultural heritage, Nanjing Yunjin struggles with inheritance and marketization. This paper explores factors affecting consumers' willingness to buy its cultural and creative products and portraits target users. Using questionnaire data, we build a prediction framework combining demographic, cognitive, aesthetic and social variables. Adopting SMOTEENN resampling and GWO optimization, the model reaches a 90.54% recall rate. SHAP analysis shows disposable income and aesthetic preference are core drivers. Modern practicality negatively impacts purchase intention, while income-aesthetic interaction exerts the strongest effect. This work supports precise marketing for intangible cultural heritage products.

Introduction:

Intangible Cultural Heritage (ICH) is a vital embodiment of cultural diversity and human creativity. As the pinnacle of Chinese silk weaving techniques, Nanjing Yunjin is renowned for its intricate patterns, luxurious materials, and profound symbolic meanings. It was first recognized as part of China's National ICH in 2006 and subsequently inscribed on UNESCO's Representative List of the Intangible Cultural Heritage of Humanity in 2009 [1]. Despite its historical and aesthetic significance, Nanjing Yunjin faces contemporary challenges, including a fragmented lineage of inheritors, high production costs, and low market penetration, which have gradually transformed it into a scarce cultural tourism resource at risk of disappearing [2].

To address these challenges, scholars and practitioners have increasingly focused on revitalizing ICH through digital preservation and the development of cultural and creative products. On one hand, technologies such as virtual reality, augmented reality, and 3D modeling have been employed to visualize and interactively present ICH, aiming to engage younger audiences [3, 4]. On the other hand, cultural intellectual property strategies have been adopted to translate ICH elements into recognizable symbolic systems, integrating them into modern consumption contexts through visual reinterpretation and cross-industry collaborations, thereby assigning them economic and educational value [5]. Notable successes in preserving Nanjing Yunjin include the development of ontology-based knowledge graphs [6] and retrieval-augmented generation-powered intelligent systems [7], which have significantly enhanced its digital dissemination.

However, existing research and practices still exhibit notable limitations. Technological applications predominantly focus on supply-side knowledge organization and cultural presentation, while insufficient attention has been paid to demand-side consumer behavior mechanisms. As a result, Yunjin-derived cultural and creative products remain confined to niche collector markets or tourist souvenirs, demonstrating low acceptance among mainstream consumer groups—particularly younger demographics—and achieving limited commercial scale. Current marketing strategies largely rely on heuristic judgments or small-sample surveys, failing to capture the complexity, nonlinearity, and high-dimensional interaction effects underlying purchase intentions in cultural consumption contexts.

Recent advances in digital economies and artificial intelligence has introduced new paradigms for consumer behavior modeling. Machine learning methods have demonstrated superior capabilities in handling high-dimensional heterogeneous data, identifying latent patterns, and predicting behavioral intentions compared to traditional statistical models. Yet, these techniques remain underutilized in studies of Nanjing Yunjin's ICH consumption. Furthermore, due to their opaque nature, high-performance machine learning models often fail to provide interpretable reasoning, thereby constraining their utility for deriving actionable business intelligence. This gap necessitates the integration of explainable artificial intelligence methodologies to address these limitations [8].

To address the research gap in understanding the factors associated with consumers' purchase intention of Nanjing Yunjin cultural and creative products, this study proposes a machine learning framework integrating predictive and explanatory capabilities. The specific objectives include: (1) identifying variables most strongly associated with high purchase intention, encompassing demographic characteristics and psychocognitive variables such as cultural identity and aesthetic preferences; (2) evaluating and comparing the predictive performance of mainstream machine learning algorithms within the domain-specific dataset; (3) leveraging the SHapley Additive exPlanations (SHAP) framework to produce model explanations at both global and instance-specific levels, revealing directional impacts and intensities of features, thereby offering data-driven decision support for precision marketing, user segmentation, and product optimization in the context of ICH cultural and creative industries.

Literature Review:

1. Cultural and Creative Product Consumption Behavior Research

Consumers' purchasing decisions for ICH-derived cultural and creative products are inherently hybrid behaviors integrating cultural value identification, aesthetic preferences, and practical utility considerations.

Cultural identity denotes a person's feeling of connection to a specific cultural group. Designs rooted in deep cultural foundations can awaken consumers' intrinsic value identification [9]. This mechanism is accounted for by the theory of planned behavior [10], which posits that when individuals perceive cultural preservation as value-aligned, recognize social approval for such actions, and feel capable of purchasing, their purchase intentions significantly increase. Empirical studies further show that cultural identity is positively associated with tourists' consumption intentions in heritage tourism contexts and serves as a significant predictor of behavioral willingness [11]. Aesthetic Preferences align with consumers' emotional expectations [12], a pathway parallel to the extended logic of the technology acceptance model [13]. Both frameworks enrich the causal chain from antecedent variables to attitudes and behavioral intentions by incorporating non-functional subjective factors. Moreover, emotional resonance and therapeutic experiences induced by visual design are often accompanied by higher levels of consumer engagement and emotional investment, which co-occur with increased likelihood of purchase decisions [14]. Self-determination theory [15] proposes a new perspective for understanding emerging consumption forms like personalized co-creation. SDT emphasizes that autonomy, competence, and relatedness are core drivers of intrinsic motivation. In artificial intelligence generated content-enabled ICH contexts, if consumers participate in pattern design, their autonomy needs are fulfilled, thereby improving product value perception and willingness to pay. Additionally, cultural products often symbolize consumers' identities and values. Research on brand community participation shows that consumer similarity significantly enhances brand attitudes and engagement intentions, aligning with the inherent communal attributes of cultural products [16]. Furthermore, practical utility value remains a critical variable influencing purchasing decisions [17]. Together with cultural and emotional value, it constitutes the triadic value framework of ICH cultural products, collectively driving consumer behavior.

Overall, existing studies have preliminarily revealed the psychological mechanisms underlying ICH cultural product consumption. However, most rely on linear methods like structural equation modeling, which fail to capture nonlinear interactions among variables and lack interpretability in model decision-making logic. This gap provides the theoretical rationale for introducing machine learning and SHAP in this study.

2. Consumer Behavior Analysis Based on Machine Learning

Amid the swift advancement of e-commerce and digital marketing, accurately predicting consumer purchase intentions benefits businesses by optimizing marketing strategies, boosting conversion rates, lowering customer acquisition costs, and simultaneously increasing customer lifetime value [18]. Machine learning methods have emerged as the predominant approach for predicting purchase intention, demonstrating superior performance over traditional consumer behavior models [19].

In study [20], an interpretable random forest model incorporating the anchoring effect was proposed to decode cognitive biases underlying consumer purchasing behaviors. This study not only improved model predictive performance but also revealed feature-specific impacts on individual decision-making through local interpretable model explanations, offering practical guidance for marketing strategy optimization and user experience enhancement. Regarding model architecture innovation, literature [21] applied support vector machines (SVM) to learn consumer preferences from sensory evaluation data, validating SVM exhibits strong robustness when applied to small-sample and high-dimensional situations. Literature [22] developed a Generative Adversarial Networks (GAN)-eXtreme Gradient Boosting hybrid model that combines GAN to augment sparse sales data with Xgboost for fine-grained sales forecasting and precision marketing strategy formulation, providing digital marketing references for online stores. Literature [23] integrated consumer review text with actual purchase behavior, employing interpretable machine learning to infer user preferences. By fusing structured transaction data with unstructured review semantics, they constructed a decision-support system balancing predictive power and transparency. Additionally, deep learning applications in consumer sentiment mining have expanded. Literature [24] utilized deep neural networks for sentiment analysis of online reviews, identifying key emotional dimensions influencing sustainable product purchase intentions.

Existing research has advanced machine learning applications in consumer behavior analysis across algorithm innovation, data fusion, interpretability, and multimodal sensing dimensions. However, predictive modeling for purchase intentions toward Intangible ICH-related cultural products, particularly integrative frameworks combining cultural identity, aesthetic perception, and digital consumption behavior, remains underexplored. Building on prior work, this study proposes an interpretable machine learning model tailored for Nanjing Yunjin consumption scenarios. It inherits methodological advantages while addressing practical demands for ICH revitalization and heritage transmission.

Method:

1. Logistic Regression Model

Logistic Regression (LR), a classical generalized linear model, is widely applied to binary classification problems due to its structural simplicity, computational efficiency, and inherent interpretability of results. In this study, LR is selected as a baseline classifier to establish the probabilistic mapping relationship between consumer features and high purchase intention.

Given a feature vector $x=(x_2, x_2,..., x_n)$, the LR model calculates the probability of the sample belonging to the high-purchase-intention class using the following formula:

$$P(y=1|x)=\frac{1}{1+e^{-(\beta_0+\beta_1x_1+...+\beta_nx_n)}} \quad (1)$$

where β_0 is the intercept term and β_i (i=1,2,...,n) are the coefficients corresponding to each feature x_i. The model estimates these parameters through maximum likelihood estimation. Despite being inherently a linear model, LR can demonstrate strong performance in many real-world scenarios when combined with proper data preprocessing, feature engineering, and effective resampling techniques.

2. Improved Grey Wolf Optimization Model

To overcome the limitations of traditional grid search or random search in high-dimensional, nonlinear hyperparameter spaces, such as inefficiency and susceptibility to local optima, this study employs the improved grey wolf optimization (IGWO) for global intelligent optimization of key hyperparameters in models like LR model. As an enhanced metaheuristic algorithm evolved from GWO, IGWO innovatively improves population initialization, convergence factor, hunting mechanism, and position update strategy to break through the bottlenecks of slow convergence, poor population diversity, and easy prematurity in the original GWO. It efficiently achieves adaptive balance between global exploration and local exploitation in complex search spaces, and quickly converges to the global optimal solution.

In IGWO, wolves are still categorized into four ranks based on fitness:

Alpha (α): The alpha wolf, representing the current optimal solution.

Beta (β) and Delta (δ): Denote the agents corresponding to the second-best and third-best fitness values in the current population.

Omega (ω): All remaining candidate solutions, which follow the top three wolves during the search.

The IGWO algorithm optimizes the original framework from four core dimensions, and its mathematical formulation is improved as follows.

(a) Sobol Sequence Initialization

To solve the problem that the random initialization of the original GWO leads to uneven population distribution and weak global exploration ability, IGWO adopts Sobol quasi-random sequence to initialize the wolf pack positions. Compared with random initialization, Sobol sequence can generate uniformly distributed initial individuals in the search space, improve the initial population diversity, and lay a foundation for accurate global optimization:

$$x_i = lb + Sobol(d) \cdot (ub - lb) \quad (2)$$

where lb and ub are the lower and upper bounds of the search space, d is the dimension of the solution, and x_i is the position vector of the i-th initial wolf.

(b) Nonlinear Convergence Factor a

The original GWO uses a linear decreasing convergence factor a, which cannot match the actual hunting process. IGWO designs a nonlinear adaptive convergence factor to realize dynamic coordination of early exploration and late exploitation:

$$a(t) = 2 \cdot (1 - \frac{t}{T_{max}})^3 \quad (3)$$

where t is the current iteration, T_{max} is the maximum number of iterations. The nonlinear decline makes a decrease slowly in the early stage (enhance global exploration) and rapidly in the later stage (strengthen local exploitation), effectively avoiding falling into local optima.

(c) Weighted Hunting Strategy

The original GWO equally treats α, β, δ wolves, ignoring the dominant role of the optimal individual. IGWO introduces adaptive weight coefficients to construct a weighted hunting mechanism, which enhances the guidance of the optimal solution:

$$x_{t+1} = \frac{w_\alpha X_\alpha + w_\beta X_\beta + w_\delta X_\delta}{w_\alpha + w_\beta + w_\delta} \quad (4)$$

The weight of α increases with iterations, strengthening the convergence guidance of the optimal solution and accelerating the algorithm speed.

(d) Adaptive Position Update with Levy Flight

To enhance the ability to jump out of local optima, IGWO integrates Levy flight into the position update equation, realizing random large-scale disturbance during the search process:

$$X(t+1) = \frac{1}{3}\sum_{k\in\{\alpha,\beta,\delta\}}[X_k(t) - A\cdot D_k] + \lambda\cdot \mathrm{Levy}(\beta) \quad (5)$$

$$A = 2a\cdot r_1 - a, D_k = |2r_2\cdot X_k(t) - X(t)| \quad (6)$$

where λ is the disturbance coefficient, $\mathrm{Levy}(\beta)$ is the Levy flight operator, and $\odot$ denotes element-wise multiplication. Levy flight can generate large-range random walks, enabling the wolf pack to jump out of local optimal regions and improve the global search performance.

3. Data Augmentation

To address the class imbalance caused by a severe shortage of high-purchase-intention samples, this study adopts the SMOTEENN hybrid resampling strategy. This method combines the advantages of oversampling and undersampling, enriching minority class information while effectively removing noise and ambiguous boundary samples, demonstrating superior efficiency and effectiveness in handling data imbalance [29]. SMOTEENN operates in two stages, SMOTE oversampling and ENN undersampling data cleaning.

(1) SMOTE Oversampling

For the minority class (high-purchase-intention samples), synthetic samples are generated along the line segments connecting neighboring instances. For any minority sample x_i, a new sample x_{new} is created by randomly selecting one of its k-nearest neighbors x_{iz}, calculated as:

$$x_{new}=x_i+\delta\cdot(x_{iz}-x_i) \quad (7)$$

Where δ is a random coefficient uniformly distributed between 0 and 1.

(2) ENN Undersampling Cleaning

The SMOTE-enhanced dataset (comprising original majority class samples and newly generated minority samples) is refined using the ENN rule, for each sample x, if the majority of its k-nearest neighbors belong to a different class, it is removed as noise or an ambiguous instance. And a sample x is retained only if its class label matches the mode of its k-nearest neighbors:

$$y=\mathrm{mode}(\{y_j|i\in i(x)\}) \quad (8)$$

In which, $N_k(x)$ denotes the k nearest neighbors of x, and mode represents the majority class label among them. Through this two-stage process, SMOTEENN expands rare positive instances while significantly improving the overall quality of the training data, laying a robust foundation for the subsequent LR model to achieve high recall.

4. Evaluation Metrics

The main goal of this research is to maximize the identification of potential consumers with high purchase intentions rather than pursuing overall classification accuracy, we employ a set of complementary binary classification metrics to comprehensively evaluate model performance.

Accuracy measures the fraction of predictions that match the true labels out of all evaluated instances. While its utility is limited in highly imbalanced datasets, it is reported as a supplementary metric.

$$\mathrm{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

Precision, the proportion of users predicted as high-intention by the model that are truly high-intention. This reflects the precision of marketing resource allocation.

$$\mathrm{Precision}=\frac{TP}{TP+FP} \quad (10)$$

Recall, the proportion of all truly high-intention users that are successfully identified by the model. This is the primary optimization objective of the study, as it directly determines the reach rate of potential high-value customers.

$$\mathrm{Recall}=\frac{TP}{TP+FN} \quad (11)$$

F1 score, the harmonic mean of precision and recall, used to measure the balance between these two metrics.

$$\mathrm{F1\ score}=\frac{\mathrm{Precision}\cdot\mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}} \quad (12)$$

Materials:

This study conducted an online survey through a questionnaire platform from March to May 2025, targeting the general public aged 18 years or older in Mainland China who had some awareness or interest in traditional culture or cultural products. A quota sampling strategy was employed, with stratified controls based on age, education, occupation, and other demographic dimensions to enhance sample representativeness. In total, 1,093 responses were obtained. After removing incomplete responses and those completed in less than 1 minute, 1,070 valid responses remained for subsequent analysis, yielding an effective response rate of 97.90%. Before completing the questionnaire, every participant was thoroughly briefed on the research goals, data handling procedures, and privacy safeguards. It was explicitly stated that the data would be used solely for academic research, handled anonymously, and contain no commercial applications. All participants completed the questionnaire voluntarily and with informed consent, ensuring compliance with academic research ethics.

Sample demographic characteristics as shown in Table 1, the sample was predominantly composed of young adults aged 18-35 years (70.5% of respondents). Female participants slightly outnumbered males, maintaining an overall balanced gender distribution. 70.2% of respondents held bachelor's degrees or higher, indicating a relatively high educational attainment level. Occupational diversity was evident, spanning students, cultural and creative industry professionals, corporate employees, and other groups. A substantial majority (62.0%) reported a monthly disposable income falling within the range of ¥3,000 to ¥9,999. Notably, only 36.2% of respondents had previously purchased traditional cultural products, highlighting the need for improved consumer conversion rates in this market.

To investigate the interrelationships between the study's constructs, this study integrates theoretical foundations from cultural identity theory, the technology acceptance model, and consumer behavior theory, alongside a synthesis of existing literature. Contextualized within the cultural and consumption dynamics of Nanjing Yunjin cultural products, questionnaire items were aggregated into 9 core research constructs and 1 outcome variable, forming a latent-variable framework for analysis. Table 2 details the measurement items and internal consistency reliability of each construct.

A 5-point Likert scale was used for all items, ranging from 1 (strongly disagree) to 5 (strongly agree). Reverse-scored items (marked R) were recoded to align directional consistency with their respective constructs. Internal consistency reliability was evaluated using Cronbach's α coefficients. A threshold of high purchase intention Q39 ≥ 4 was defined for outcome variable classification. Results showed Cronbach's α values ranging from 0.61 to 0.92, with constructs such as aesthetic (α = 0.86) and personalization willingness (α = 0.92) exceeding the 0.85 benchmark, indicating robust reliability. The measurement model demonstrated adequate psychometric properties, supporting subsequent analytical rigor.

Table 1. Sample Demographic Characteristics (N = 1,070

Item	Category	Frequency	Percentage
Q1 age	18–25 years	445	41.59%
	26–35 years	309	28.88%
	36–45 years	147	13.74%
	46–55 years	119	11.12%
	56 years and above	50	4.67%
Q2 gender	male	493	46.07%
	female	550	51.40%
	prefer not to disclose	27	2.52%
Q3 education	high school or below	112	10.47%
	associate degree	207	19.35%
	bachelor degree	540	50.47%
	master degree and high	211	19.72%
Q4 occupation	student	279	26.07%
	cultural/ creative industry	161	15.05%
	freelancer	40	3.74%
	corporate/public sector	500	46.73%
	other	90	8.41%
Q5 income	< ¥1,000	107	10.00%
	¥1,000–¥2,999	96	8.97%
	¥3,000–¥5,999	321	30.00%
	¥6,000–¥9,999	342	31.96%
	≥ ¥10,000	198	18.50%
	prefer not to disclose	6	0.56%
Q6 visited museum	yes	640	59.81%
	no	430	40.19%
Q7 articraft purchased	yes	387	36.17%
	no	683	63.83%

Table 2. Composition of Research Constructs and Reliability Analysis

Construct	Items	Cronbach's α
cultural knowledge	Q8 I have some understanding of the history and culture of Yunjin. Q9 I believe Yunjin is an important representation of China's fine traditional culture. Q10 Yunjin patterns possess high artistic value.	0.75
cultural value	Q11 Yunjin deserves better protection and inheritance. Q12 I am willing to actively learn about Yunjin-related knowledge.	0.61
aesthetic	Q13 The colors and patterns of Yunjin give me a sense of aesthetic appreciation. Q14 I find Yunjin designs extremely exquisite. Q15 The visual style of Yunjin is appealing to me.	0.86
modern fit	Q16 I think Yunjin can be integrated into modern life. Q17 Yunjin is too complex and difficult to understand. (R) Q18 Yunjin elements are suitable for contemporary design. Q19 Yunjin should not remain only in museums but should reach the general public.	0.68
aigc acceptance	Q20 I am open to AI-generated Yunjin patterns. Q21 AIGC technology helps innovatively promote Yunjin culture. Q22 Using AI to design Yunjin diminishes its "sacredness." (R) Q23 I would be willing to try Yunjin products co-designed with AI assistance.	0.83
price sensitivity	Q24 A reasonable price for Yunjin cultural and creative products should be within ¥100. Q25 Even if I like the Yunjin design, I would not buy it if it costs more than ¥300. (R) Q26 I am willing to pay a 20% premium for products certified as "Intangible Cultural Heritage Handicrafts." Q27 The price of Yunjin products should reflect their cultural value, not just functional utility.	0.77
social influence	Q28 I would recommend Yunjin cultural and creative products to friends. Q29 If recommended by an influencer/KOL, I would be more willing to try Yunjin products. Q30 I would give Yunjin products as gifts to foreign friends. Q31 Sharing Yunjin-related content on social media enhances my sense of cultural identity.	0.81
sustainability concern	Q32 I prefer Yunjin derivatives made from eco-friendly materials. Q33 Fair compensation for Yunjin inheritors significantly influences my purchase decision. Q34 I oppose using Yunjin patterns on low-quality fast-moving consumer goods (e.g., disposable tableware). (R)	0.75
personalization willingness	Q35 I hope to input keywords (e.g., birthday, zodiac sign) to generate personalized Yunjin patterns. Q36 Participating in online Yunjin pattern design activities would increase my willingness to buy. Q37 I am willing to pay a higher price for a Yunjin product I designed myself. Q38 Yunjin brands should accept user-submitted patterns and mass-produce outstanding designs.	0.92
high purchase	Q39 Overall, I hold a positive attitude toward purchasing Yunjin-related products.	—

Experiments and Results Analysis:

1. Performance Assessment and Ablation Study

To identify key factors influencing consumer high purchase intention, this study conducted Spearman's rank correlation analysis between the dependent variable (high purchase) and 16 potential explanatory variables. As illustrated in Figure 1, the analysis revealed that income exhibited the strongest positive correlation with high purchase ($r=0.41$, $p<0.01$), indicating that Nanjing Yunjin is perceived as a premium cultural product, with its core consumer base primarily comprising high income individuals. Age also showed a significant positive correlation with high purchase intention ($r=0.20, p<0.01$), suggesting that middle-aged and elderly consumers demonstrate stronger willingness to purchase high-value Yunjin products. Additionally, three variables displayed statistically significant negative correlations with high purchase ($p<0.01$):

- Price sensitivity: the correlation coefficient of −0.21 indicates that consumers with higher price sensitivity exhibit lower high-purchase intention. This finding confirms that the core consumer group for premium Yunjin products is price-insensitive, prioritizing cultural value and craftsmanship scarcity over cost, a characteristic aligned with luxury cultural product consumption.
- Modern Fit: The correlation coefficient of −0.08 reveals that stronger perceptions of Yunjin's "compatibility with modern life"

correspond to lower high-purchase intention. This highlights the demand logic of the core consumer group: they view Yunjin not as a practical daily-use item but as a cultural collectible, prioritizing traditional authenticity and intangible cultural heritage attributes over utilitarian functions.

- Personalization willingness: The correlation coefficient of −0.18 implies that consumers willing to pay premiums for personalized customization exhibit relatively lower high-purchase intention. This suggests that the core consumer group values standardized, classic designs of traditional craftsmanship, perceiving customization as a potential threat to cultural authenticity and collectible value.

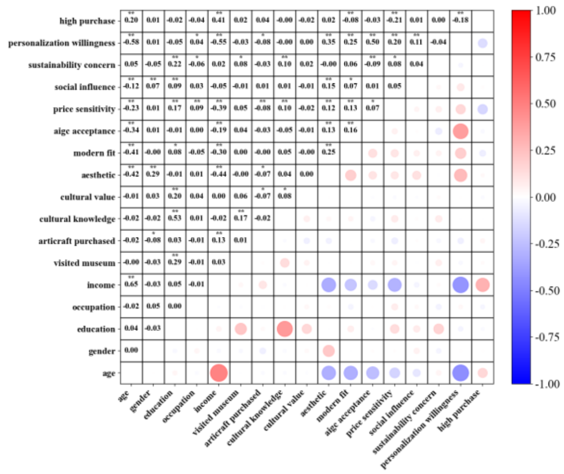

Figure 1. Spearman correlation matrix of high purchase intention and influencing factors

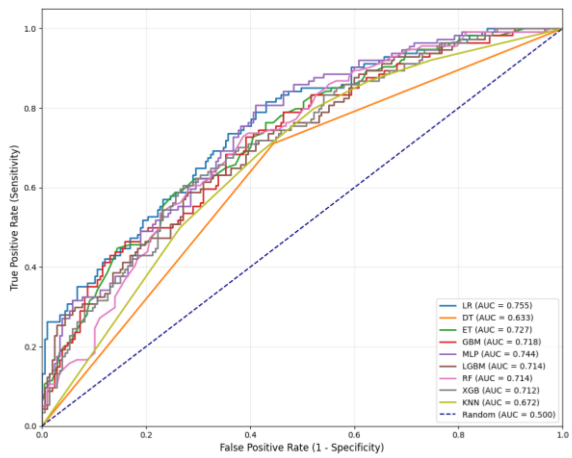

Figure 2. ROC curves of models under SMOTEENN resampling

Given the highly imbalanced nature of the high purchase intention class, which constitutes the minority group, accuracy is an unreliable performance metric. We therefore prioritize recall, defined as the ability to correctly identify true high-intent consumers, because it is critical for effective targeted marketing and resource allocation in the promotion of premium cultural products. We evaluate nine classical machine learning models: Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Gradient Boosting Machine (GBM), eXtreme Gradient Boosting (XGB), LightGBM (LGBM), Extremely Randomized Trees (ET), k-Nearest Neighbors (KNN), and Multilayer Perceptron (MLP). Each model is tested under six resampling conditions, including the original imbalanced dataset as well as SMOTE, Borderline-SMOTE (BorSMOTE), ADASYN, SMOTETomek Links, and SMOTEENN. For every configuration, the data are split into training and test sets using a stratified 7:3 partition. Resampling is applied exclusively to the training set to prevent data leakage, and models are trained on the resulting balanced samples. Performance is assessed on the original, unmodified test set, with recall reported as the primary metric. To account for sampling variability, we estimate 95 percent confidence intervals for recall using non-parametric bootstrapping based on 1,000 resamples of the test predictions.

As shown in Table 3, the combination of LR and SMOTEENN achieves the highest recall of 0.9054, substantially outperforming all other model-resampling configurations. This result suggests that hybrid resampling methods such as SMOTEENN, which simultaneously generate synthetic minority instances and remove noisy or borderline majority samples, are especially effective in this context. Other notable results include MLP with SMOTE (recall = 0.718) and KNN with ADASYN (recall = 0.677). In contrast, tree-based ensemble methods, including RF and XGB, show relatively limited gains from resampling, indicating that their inherent robustness to class imbalance may be undermined by overfitting to synthetic data.Having identified SMOTEENN as the optimal data resampling strategy, we further evaluated the comprehensive classification performance under this configuration. As shown in Table 4, all metrics are reported as the mean and standard deviation (SD) derived from 1,000 bootstrap resamples of the test set predictions, reflecting the stability of the estimates. The results indicate that LR achieves the highest recall at 0.9054 ± 0.0390, substantially outperforming all other models, reaffirming its strong capability in identifying high purchase intention users after resampling. However, its precision is relatively low (0.2670 ± 0.0324), suggesting a tendency to misclassify many non-high-intent instances as positive, a typical trade-off when prioritizing recall in highly imbalanced settings. MLP and KNN also demonstrate strong recall performance (0.8503 ± 0.0509 and 0.7535 ± 0.0596, respectively), albeit with similarly limited precision. In contrast, ensemble tree-based models exhibit more balanced overall performance. LGBM attains the highest accuracy (0.7391 ± 0.0243) and F1 score (0.4326 ± 0.0491), while GBM and ET achieve F1 scores close to 0.41, indicating a better balance between precision and recall. In summary, for the present task where maximizing the identification rate of high purchase intention consumers is the primary objective, the LR and SMOTEENN combination emerges as the optimal choice.

To evaluate the overall discriminative ability of the models across different decision thresholds, we plot the Receiver Operating Characteristic (ROC) curves for all nine machine learning algorithms under the SMOTEENN resampling strategy. As shown in Figure 2, the area under the curve (AUC) values range from 0.501 to 0.890, indicating varying degrees of classification performance. LR model achieves the highest AUC of 0.890, demonstrating its strong capacity to distinguish high purchase intention consumers from others, even when applied to rebalanced data.

Table 3. Recall performance of different models under different resampling strategies

Mode	Original	SMOT	BorSM	ADAS	SMOTETo	SMOTEE
LR	0.1333	0.5859	0.5667	0.5674	0.5859	0.9054
DT	0.2278	0.3414	0.3030	0.3200	0.3414	0.5846
ET	0.1714	0.2082	0.1884	0.2252	0.1692	0.6069
GBM	0.2093	0.3222	0.2257	0.3031	0.3028	0.6272
MLP	0.1146	0.7180	0.3207	0.3782	0.6622	0.8503
LGB	0.2666	0.2454	0.2274	0.1877	0.1505	0.6067
RF	0.0769	0.1697	0.1691	0.1502	0.1316	0.5492
XGB	0.2268	0.1691	0.1704	0.1883	0.1506	0.5115
KNN	0.1529	0.5651	0.5841	0.6774	0.5651	0.7535

Table 4. Classification performance of models using SMOTEENN

Models	Accuracy		Precision		Recall		F1 score	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
LR	0.5744	0.0266	0.2670	0.0324	0.9054	0.0390	0.4114	0.0399
DT	0.6671	0.0264	0.2673	0.0405	0.5846	0.0680	0.3655	0.0468
ET	0.7018	0.025	0.3001	0.0425	0.6069	0.0665	0.4002	0.0472
GBM	0.7122	0.0249	0.3137	0.0434	0.6272	0.0637	0.4168	0.0473
MLP	0.5715	0.0259	0.2577	0.0325	0.8503	0.0509	0.3946	0.0406
LGBM	0.7391	0.0243	0.3379	0.0466	0.6067	0.0656	0.4326	0.0491
RF	0.6988	0.0263	0.2853	0.0451	0.5492	0.0701	0.3741	0.0504
XGB	0.7048	0.0243	0.282	0.044	0.5115	0.0664	0.3621	0.0482
KNN	0.4887	0.0268	0.2089	0.0284	0.7535	0.0596	0.3262	0.0374

To further enhance model performance in identifying high purchase intention consumers, we introduce the GWO to globally search and optimize key hyperparameters of nine classical machine learning models. As shown in Table 5, each model's hyperparameters were tuned within predefined ranges, yielding optimal configurations. To assess how effectively the optimization process performs, we conducted a 10-fold stratified cross-validation assessment comparing the default and GWO-optimized versions of each model on recall performance. Figure 3 presents boxplots illustrating the distribution of recall scores across all folds. GWO optimization significantly improves the recall of most models: LR, DT, ET, LGBM, XGB, and KNN all achieve notable gains, with the optimized LR model still delivering the best performance. GWO effectively explores complex nonlinear parameter spaces and helps models escape local optima, thereby enhancing their ability to capture minority-class patterns in imbalanced datasets. All models adopted SMOTEENN resampling. Default models represent baseline models without GWO hyperparameter optimization; GWO-optimized models were optimized using the grey wolf optimizer algorithm. Boxes display bootstrapped recall values.

After hyperparameter optimization, we applied the optimal parameter configurations obtained by GWO to evaluate all nine models on the original, unresampled test set and generated their respective confusion matrices, as shown in Figure 4. The results indicate that all models effectively identify high purchase intention users (the positive class). Specifically, LR model achieves a true positive (TP) count of 48 and only 5 false negatives (FN), demonstrating exceptionally high recall. All other models exhibit fewer TP than LR mdoel.

As shown in Figure 5, the experimental results show that the TP values under the four configurations are as follows: the baseline model (Group A) achieves a TP of 7; after applying SMOTEENN (Group B), TP significantly increases to 45; with GWO optimization alone (Group C), TP reaches 14; and the full pipeline combining SMOTEENN and GWO optimization (Group D) achieves the highest TP value of 48. These results indicate that SMOTEENN plays a critical role in enhancing the model's ability to identify high purchase intention users, boosting TP from 7 to 45, a substantial improvement. Although GWO optimization also contributes to increasing TP, its effect is notably less pronounced compared to SMOTEENN. The combination of SMOTEENN resampling and GWO-based hyperparameter tuning effectively maximizes the TP value, ensuring the model achieves excellent minority class detection capability.

Table 5. Search space definition and GWO-optimized hyperparameter settings

Model	Hyperparameters	Search Range	Optimal Value
LR	C	[0.01, 10]	0.02
	penalty	['l1', 'l2']	'l2'
DT	max_depth	[3, 20]	4
	min_samples_split	[2, 20]	13
ET	n_estimators	[50, 300]	197
	max_depth	[3, 20]	12
GBM	n_estimators	[50, 300]	134
	max_depth	[3, 12]	3
	learning_rate	[0.01, 0.3]	0.0382
MLP	hidden_layer_sizes	[10, 100)]	48
	alpha	[0.01, 0.1]	0.0343
	learning_rate_init	[0.0001, 0.01]	0.00206
LGBM	n_estimators	[50, 300]	145
	max_depth	[3, 12]	6
	learning_rate	[0.01, 0.3]	0.0171
RF	n_estimators	[50, 300]	267
	max_depth	[3, 20]	11
XGB	n_estimators	[50, 300]	60
	max_depth	[3, 12]	2
	learning_rate	[0.01, 0.3]	0.0556
KNN	n_neighbors	[3, 20]	12
	weights	['uniform', 'distance']	'uniform'

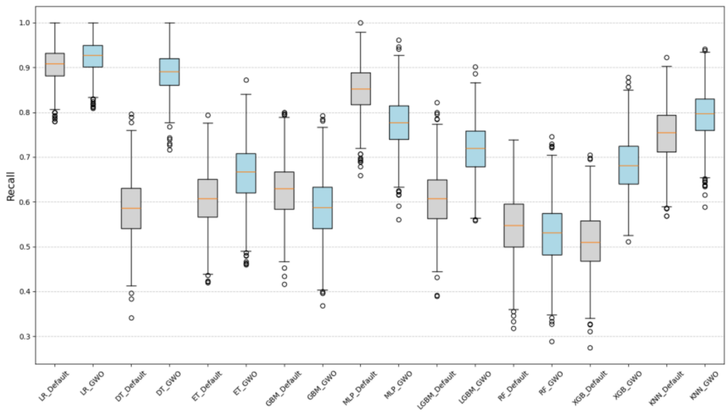

Figure 3. Recall distribution of different classification models.

To gain an in-depth understanding of the decision-making logic of the model in identifying users with high purchase intention, we adopted SHAP values to conduct an explainability analysis of the optimal model. As shown in Figure 6, SHAP values visualize the impact of each feature on the model output in the form of a dot plot: positive values (on the right side) indicate that a higher value of the feature is more likely to predict "high purchase intention", while negative values (on the left side) suggest the opposite. Income emerges as the core driving factor influencing consumers' purchase intention, accounting for 27.51% of the total feature importance weight, which is significantly higher than that of other features. Moreover, this feature exhibits a prominent bidirectional effect: when consumers fall into the high-income bracket, the corresponding SHAP values are highly positive, which significantly increases the predicted probability of high purchase intention; conversely, low-income levels are associated with negative SHAP values, exerting a strong inhibitory effect on purchase intention. Furthermore, aesthetic preference (14.65%) and AIGC acceptance (7.93%) also demonstrate positive driving effects. This indicates that the degree of aesthetic fit of products and consumers' openness toward AI-generated content are important positive factors affecting purchase intention. All other features contribute less than 7% to the total importance weight, exerting a relatively weak overall impact on purchase intention. In this consumption scenario, income level serves as the primary boundary condition determining purchase intention, while aesthetic preference for Yunjin and acceptance of AIGC technology act as the core positive moderating factors.

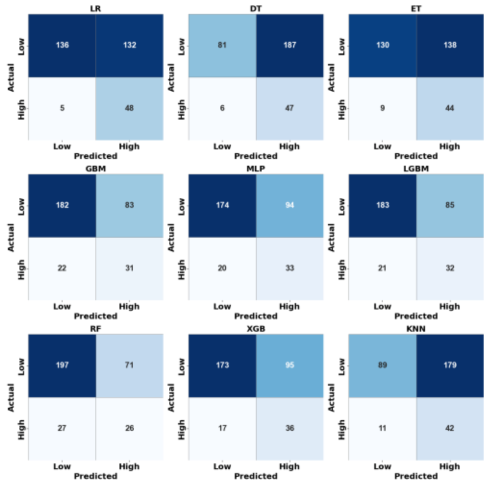

Figure 4. Confusion matrices of optimized models on the original test set

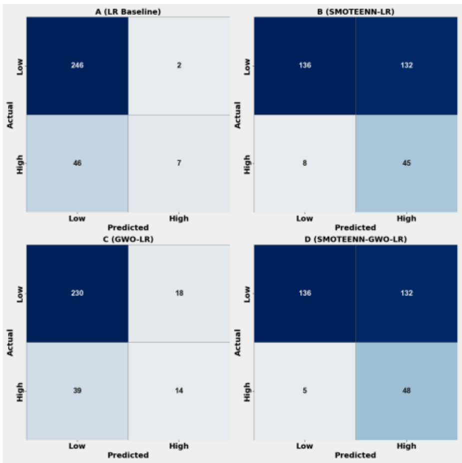

Figure 5. Ablation study confusion matrices of different model configurations

This study further analyzed the top 6 features influencing high purchase intention as shown in Figure 7. For income, low levels correlate with negative SHAP values, significantly inhibiting purchase intention; conversely, incomes above 10,000 yuan drive SHAP values to highly positive levels, sharply boosting the predicted probability of high purchase intention, with a high R2 < 0.05 confirming income's strong explanatory power and statistical significance. Aesthetic preference (aesthetic) acts as a stable emotional driver: the SHAP dependence plot shows a monotonically positive relationship where higher recognition of Yunjin's color and pattern aesthetics corresponds to more positive SHAP values, steadily promoting purchase intention, and its high R2and statistical significance highlight aesthetic value as a key emotional anchor for Yunjin products, necessitating prioritized visual aesthetic communication in design and marketing. AIGC acceptance (aigc) is an emerging enabling factor with a positive nonlinear relationship, medium-to-high acceptance rapidly lifts SHAP values and amplifies purchase intention (low acceptance has weak < 0.05), verifying that integrating AIGC with traditional cultural products drives young consumers decisions and offers an innovative marketing breakthrough. Both price sensitivity and sustainability concern exhibit a significant positive correlation with SHAP values, which means that the higher the consumers' price sensitivity and their attention to product sustainability, the more strongly they positively drive the increase in purchase intention. In contrast, modern fit shows a significant negative correlation with SHAP values: the higher the value of this feature, the weaker its positive effect on purchase intention.

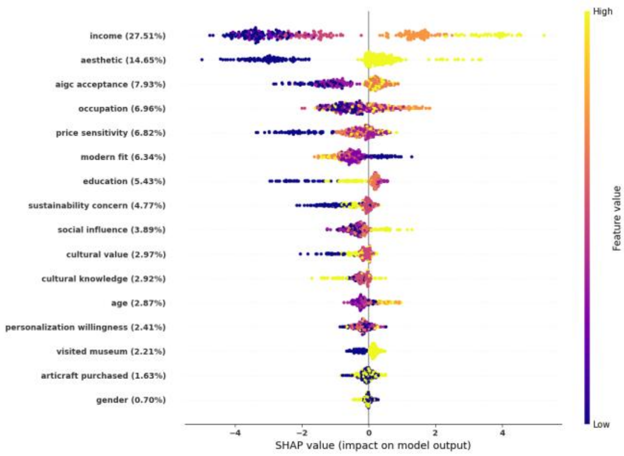

Figure 6. Feature importance analysis

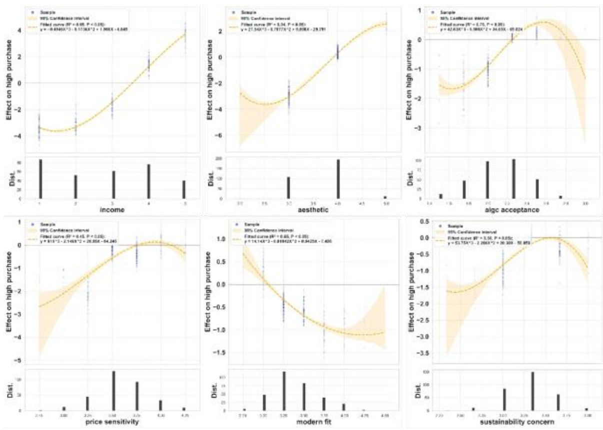

Figure 7. SHAP-based interpretation of feature contributions

The positive tendency observed in the SHAP dependence plot represents the conditional effect after controlling for other features, whereas the Spearman correlation only reflects a bivariate relationship. The divergence in sign is statistically expected and not contradictory.

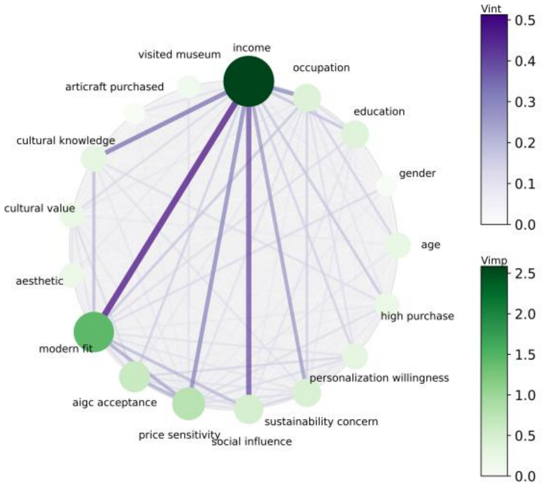

Figure 8. Correlation network of features influencing purchase intention

As illustrated in Figure 8, the network graph of feature importance (Vimp) and feature interaction (Vint) visually reveals the following patterns: The size and color intensity of nodes reflect feature importance, with larger sizes and darker hues indicating higher importance. The thickness and color intensity of connecting lines represent interaction strength, where thicker lines and darker colors signify stronger interactions. Furthermore, the top 10 core feature combinations are summarized in Table 6.

Table 6. Top 10 Core Feature Combinations

Feature 1	Feature 2	Interaction value
income	modern fit	0.5128
income	social influence	0.4104
income	cultural knowledge	0.3531
income	price sensitivity	0.3167
occupation	income	0.3081
income	sustainability concern	0.2699
modern fit	price sensitivity	0.2442
aigc acceptance	price sensitivity	0.2355
modern fit	social influence	0.2083
cultural knowledge	modern fit	0.2068

Income emerges as the central hub in the feature interaction network, exhibiting significantly stronger interactions with other features compared to other variables. The interaction value between Income and Modern Fit reaches 0.5128 (the highest in the full sample), while interactions with Social Influence, Cultural Cognition, and Price Sensitivity all exceed 0.3. This demonstrates that Income is not only an independent critical factor influencing purchase intention but also amplifies the effects of other features on purchase intention through strong interconnections, further solidifying its dominant role in the purchase intention framework.

The interaction value between occupation and income (0.3081) is notably high, reflecting that income disparities across occupational groups intensify attitude polarization toward Yunjin products. Additionally, the interactions between modern fit and price sensitivity (0.2442), as well as AIGC acceptance and price sensitivity (0.2355), are statistically significant. This indicates that for groups with high acceptance of "Yunjin's compatibility with modern life" or "AIGC-integrated cultural products," the impact of price sensitivity on purchase behavior is further amplified.

Finally, the mediating role of cultural cognition is validated, the interaction value between cultural cognition and modern fit (0.2068) is relatively high. Combined with its interaction with aesthetic preference, this supports the conclusion that "Cultural Cognition serves as the foundation for emotional traits such as aesthetic preference and modern Fit." It also suggests that enhancing consumers' cultural understanding of Yunjin can indirectly strengthen purchase intention through synergistic effects with other features.

Conclusion:

This study employs machine learning models combined with SHAP interpretability analysis to deeply investigate key factors influencing consumer purchase intention toward Nanjing Yunjin intangible cultural heritage products, yielding the following major findings: (1) machine learning model efficacy, the GWO-optimized logistic regression model achieves high predictive accuracy, with a test set recall rate of 90.54%. (2) Core driving factors, monthly disposable income (27.51% contribution) and Yunjin aesthetic preference (14.65% contribution) emerge as the dual core drivers of purchase intention. (3) Technological empowerment, AIGC acceptance (7.93% contribution) demonstrates a significant positive effect, indicating that integrating AI technology into Yunjin design enhances consumer receptivity and opens new pathways for innovative development in intangible heritage cultural products.

This study's practical implications underscore that cultural enterprises should prioritize strategic targeting of high-income demographics with strong aesthetic sensitivity to optimize user profiling, while concurrently enhancing communication of Yunjin's cultural significance and immersive aesthetic experiences. Enterprises are further advised to actively explore AIGC integration within Yunjin design processes to leverage technological innovation, all while rigorously mitigating excessive commercialization risks to preserve cultural authenticity. By implementing these interconnected strategies, targeted audience segmentation, value-driven storytelling, technology-enabled design, and authenticity preservation, cultural enterprises can systematically strengthen consumer engagement and align with the data-driven insights revealing nonlinear decision-making pathways. This integrated approach not only validates the research's methodological framework for heritage revitalization but also establishes a replicable model for sustainable commercialization of intangible cultural heritage projects globally.

Limitations:

While this study offers a novel interpretable machine learning framework for understanding consumer purchase intention toward ICH products, several limitations should be acknowledged.

First, the data were collected through a cross-sectional online survey, which captures associations rather than causal relationships. Although our model identifies key predictors, such as income, aesthetic preference, and attitudes toward modern adaptability, these variables cannot be interpreted as causal drivers of purchase intention. Future research could address this limitation by employing experimental designs or longitudinal panel studies to track changes in intention and actual behavior over time. Second, the sample exhibits notable demographic skew, over 70% of respondents were aged 18–35 and held a bachelor's degree or higher. While quota sampling was used to align with certain national demographics, this composition likely overrepresents digitally literate, urban, and culturally engaged individuals. As a result, findings may not generalize to older generations, less-educated populations, or rural communities with different exposure to or perceptions of ICH. To enhance external validity, future investigations should recruit more heterogeneous samples across age, education, geographic region, and socioeconomic status. Comparative modeling across subgroups could further reveal how purchase intention mechanisms differ across cultural or generational lines. Third, although the SMOTEENN-GWO-LR pipeline achieved high recall, critical for identifying rare high-intention consumers, it yielded relatively low precision, indicating a non-negligible rate of false positives. In real-world marketing applications, this trade-off warrants careful consideration. The dependent variable of consumer purchase intention is measured relying solely on a single Likert-scale survey item. Single-item measurement inherently lacks sufficient internal reliability and may compromise construct validity compared with multi-item composite scales. To verify the stability of empirical results, we have supplemented a sensitivity analysis with an alternative classification threshold of Q39 ≥ 4.5; the feature importance ranking remains consistent, which safeguards the reliability of core conclusions. Subsequent research can design a multi-item measurement scale to construct a composite purchase intention index and revalidate the prediction framework. Future work could integrate cost-sensitive learning or decision-theoretic thresholds tailored to specific business objectives. Addressing these limitations will not only strengthen the robustness of predictive models for ICH consumption but also deepen our understanding of how tradition and technology intersect in contemporary cultural markets.

Conflict of interest:

The authors of this publication declare there are no competing interests.

Data availability statement:

The data supporting this study are available from the corresponding author upon reasonable request.

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