# Using XGBoost to Evaluate the Impact of Tourism Destination Marketing Campaigns on Tourists' Psychological Motivations and Behavioral Intentions

**Yutong Yang**
International Tourism Management, Macau University of Science and Technology, Macau 999078, China
Corresponding author: Yutong Yang (e-mail: chloe82168@163.com)

**ABSTRACT** With the rapid development of mobile communication networks and digital information dissemination technologies, tourism destination marketing increasingly relies on wireless media platforms to influence tourists' psychological responses and behavioral decisions. To reveal the nonlinear mechanisms underlying this process, this study proposes a multi-level attribution framework integrating Extreme Gradient Boosting (XGBoost) and SHAP analysis. Using 4,826 field survey samples combined with real marketing logs, the framework models the relationships among marketing activities, psychological motivations, and behavioral intentions while quantifying feature contributions and mediation effects. The results demonstrate that short-video exposure exerts the strongest influence on recommendation intention among first-time out-of-province tourists, whereas festival activities more effectively promote revisit intention among repeat visitors. Heterogeneity analysis further reveals age-dependent differences in motivational pathways, with social identity dominating younger groups and escapism becoming more influential among older tourists. The proposed interpretable machine learning framework provides robust support for precision marketing and behavioral prediction under data-rich environments. Moreover, its methodology offers potential value for communication-assisted intelligent service systems and multimedia information dissemination scenarios, where reliable digital content transmission and user behavior modeling are essential for optimizing personalized interaction strategies.

**INDEX TERMS** tourism destination marketing, XGBoost, shap analysis, behavioral intention, digital information dissemination

## I. INTRODUCTION

THE competitiveness of tourist destinations depends more and more on accurate insights relating to the deep-psychological motivations of tourists [1, 2]. As a crucial factor, marketing plays a significant role not only in traffic conversion but also in activating internal motivations, including emotional resonance, identity recognition, and meaning construction, which leads to revisit, recommend, and consume. This foundational principle of leveraging deep-psychological drivers is directly transferable, underscoring the necessity for the industry to similarly target emotional connection and identity recognition in its branding to achieve lasting consumer loyalty and repeated high-value purchasing [3,4]. Among the high volume of information and homogenized experiences, which high-impact marketing design elements should be identified and how to unveil the design elements' paths in action has become a major concern in the tourism management science [5,6]. Interpretable causality attribution models are developed to help a leap from surface association to mechanism analysis, which can provide dynamic and personalized strategic support for destinations and improve the efficiency of resource allocation as well as long-term brand value enhancement. It should be noted that the similar driving mechanism modeling techniques have been applied in the analysis of consumer behavior in order to forecast pattern preferences and purchase choices, demonstrating the potential for application across different domains.

Existing evaluation systems mostly rely on linear structural equations or logistic regression models, making it difficult to capture the asymmetric, threshold-type, and higher-order interaction effects between marketing variables and psychological constructs [7,8]. For example, discount incentives may only significantly increase the willingness to share when emotional resonance reaches a certain level, and such conditional dependencies cannot be fully revealed by traditional parametric models [9,10]. Some studies have attempted to apply machine learning methods, but they remain at the level of predictive performance optimization, lacking a systematic interpretation of the evolution of feature importance and failing to transform model outputs into interpretable behavior-driven paths [11,12]. Meanwhile, it is worth noting that the majority of empirical analyses overlook structural heterogeneity among the tourists, and treat consumers of different ages, travel purposes, and cultures as the same unit, hampering the external adaptability of strategic implications [13,14]. Another limitation comes from single data source, as it too heavily depends on cross-sectional surveys [15,16], and lacks time synchronization and behavior tracing with real marketing campaign data, which leads to exogenous biases [17]. In addition, psychological motivations are commonly represented as a static latent variable without considering the dynamics of activation intensity, which varies by the advertising themes [18-20]. Taken together, such limitations challenge the fine-grained dissection of the causal chain of "which activity-eliciting which motivations-resulting in which behavior", constraining the formulation and empirical validation of specific and dynamic marketing instruments. The innovation of this paper lies in constructing a multi-level causal attribution framework, which, through two-stage XGBoost-SHAP modeling, systematically decouples the non-linear transmission path of 'marketing activities $\rightarrow$ psychological motivation $\rightarrow$ behavioral intention'. Its uniqueness is reflected in: (1) In terms of methodology, the SHAP value product mechanism is used to quantify the mediation effect, breaking through the assumptions of the traditional linear mediation model; (2) In terms of data, it integrates large-scale field questionnaires and real marketing behavior logs for the first time, realizing the spatiotemporal alignment of psychological and behavioral data at the individual level, thereby supporting fine-grained attribution. It also includes a heterogeneity testing such as across scenic areas and population groups, to identify the boundary conditions of driving patterns disseminated by tourists' demographic and spatial features. The framework is driven by a fusion dataset that includes comprehensive field surveys and real marketing logs of subscribers, which guarantees external validity. The findings offer a practical attribution instrument for tourism management to support the transition from experience-based towards data-driven precision marketing decision, and enrich the theoretical application depth of ML in tourism behavioral science. Furthermore, this instrument's robust, data-driven methodology provides an immediately transferable framework, enabling the industry to move beyond traditional market intuition toward precision marketing and data-backed decision-making in product development and global consumer outreach.

## II. METHODS

### A. DATA ACQUISITION AND SAMPLE DESIGN

The study duration is from April 2023 to September 2024, and three representative tourist cities in China (West Lake Scenic Area in Hangzhou, Datang Everbright City in Xi'an, and Kuanzhai Alley in Chengdu) are selected. These three places reflect natural landscape, historical and cultural site, and urban leisure site, respectively, and they have obviously dispersed geographical distribution and diverse cultural background, which enhance the external generalizability of this study sample. The data collection adopts the stratified random sampling method, and the sampling size is firstly allocated according to the proportion of the average daily visitor flow in each scenic spot, so as to ensure that the structural distribution of the sample is consistent with that of the actual visitor flow. A total of 5,300 questionnaires are planned to be distributed, with a 10% redundancy reserve for invalid responses. Field implementation uses online QR (Quick Response) code scanning and offline interception. Permanent access points are established at the rat population main gates and exits, at service points, and at core activity nodes, with guidance provided to tourists filling out electronic questionnaires. A commemorative voucher is granted upon completion as an encouragement for participation. The questionnaire contains also demographic items on gender, age, place of origin and visiting frequency and employs a seven-point Likert scale to capture psychological perceptions and behavioral reactions, making the measurement more robust. This study was approved by the Ethics Committee of Macau University of Science and Technology, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form. IDs of encrypted type are automatically generated per individual identity and synchronized to local tourism marketing management system of scenic spot that distinguishes individuals. This system pulls digital behavior logs for each respondent two weeks prior and two weeks after their visit. Short video platform exposure number, social media interaction behavior, KOL (Key Opinion Leader) contents reached records, offline advertising geofencing entry events, coupons issued and redeemed status are included in the log. The time window design is based on consumer decision response cycle theory to determine a potential lag effect. All data were tightly matched at the ID level, providing multi-source information at the individual level, thereby significantly mitigating the interference from recall bias and marketing-behavior asynchronicity. Although the impact of unobserved exogenous shocks (such as extreme weather or competitive activities) cannot be completely ruled out, this design maximizes the reliability of causal inferences within empirically feasible limits. It is controlled by full-process monitoring, including rejection of samples with abnormal answer time, samples with answers in a regular pattern and duplicated IP addresses. Finally, 4,826 questionnaires which are positive and logical valid are retained, with an effective recovery rate of 91.3%. This data structure ensures spatiotemporal alignment of perceived and actual behavior, yielding a high-quality baseline data set for nonlinear attribution analysis.

Figure 1 illustrates the sample distribution across gender, age, origin and visit type. Gender is almost equal, with a slightly higher share of women – in line with their leading role in tourism decisions. The majority of respondents are between the ages of 18 and 45, indicating that the sample consists predominantly of young travelers, who are digitally engaged and travel independently. More than half of the visitors originate from outside the province, highlighting the trans-regional attraction of the sites and the necessity for region-specific promotion. There are more first-time visitors than repeat ones by a large margin, allowing for a strong evaluation of one-time marketing effects. These figures correspond to the types of sites chosen: historical and urban leisure sites bring in more young, out-of-province, first-time visitors, and natural sites have more local repeat visitors. This facilitates meaningful heterogeneity analysis in a realistic environment.

### B. DEFINING OPERATIONAL VARIABLES FOR MARKETING ACTIVITIES, PSYCHOLOGICAL MOTIVATIONS, AND BEHAVIORAL INTENTIONS

Constant systems respect measurability, traceability, and verifiability to enable the theoretical structure to be practically applied [21,22]. Marketing campaigns can be observed within 6 dimensions: (1) video length, which includes short video exposure frequency derived from platform logs (e.g., TikTok, Kuaishou) and time decay as a weight to indicate information contact intensity [23,24]; (2) number of KOL collaborates, according to active interaction (no passive exposure) with tourist creators on social media [25,26]; (3) rate of festival events cleaning or in ticketing and check-in systems over visitors duration of stay; (4) interaction with social media (preferential criteria): total of likes, reposts, and comments for a page in a destination's official account/page among page views [27,28]; (5) density of offline advertising coverage, estimated by GIS for monitoring tourist exposure to adverts at advertisings installation places (e.g. digital screens, bus stops); (6) intensity of coupon send-outs, computed by how many and the denomination of the targeted promotional vouchers a user is given. It should be noted that this study operationalizes marketing activities as the intensity of objective exposure to actual visitor contact (rather than self-reported perceived intensity) for two reasons: first, log data avoids recall bias and common method bias; second, the activation of psychological motivation depends primarily on actual contact, not subjective misjudgment. In subsequent analysis, we verified the consistency between log indicators and subjective perceptions by conducting a correlation test between SHAP values and the "marketing perception" item in the questionnaire ($r > 0.61$, $p < 0.001$), thus supporting their reasonableness as effective proxy variables.

Psychological motivation is a seven-factor model based on the Enhanced Travel Motivation Scale, including novelty seeking, escapism, social identification, cultural exploration, relaxation, self-actualization, and family companionship; each factor contains 4-6 Likert scale items ($\alpha > 0.82$). Items are optimized for reliability and validity, and low-discrimination items are eliminated using item response theory [29,30]. Behavioral intentions are measured by three indicators: the intent to revisit and to recommend (self-rated on a 0-10 scale) [31,32], and daily spending per capita in RMB, compiled by POS and mobile payment records to control for subjective bias. All variables are cross-validated: subjective reports are verified with objective logs, and inconsistent samples are manually examined to ensure data authenticity and the stability of the measurements.

### C. CONSTRUCTING DRIVING EFFECT IDENTIFICATION MODELS BASED ON XGBOOST

The model construction focuses on the identification of nonlinear driving relationships and uses the XGBoost algorithm to model behavioral intentions. The three behavioral intentions are treated as independent output variables, with the average daily consumption amount as a continuous target variable, and the XGBoost regression framework is used for fitting. The revisit intention and recommendation intention are transformed into binary classification tasks, with a threshold of 7 points and above assigned to the high intention group [33,34], and the rest assigned to the low intention group, and XGBoost classification training is performed. The input features include 13 dimensions in total, including six types of marketing activities and seven psychological motivations [35]. All variables are standardized, and outlier truncation is performed to ensure numerical stability.

The model training process incorporates a regularization mechanism to suppress overfitting. The objective function consists of a prediction error term and a tree structure complexity penalty term.

$$L = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{1}$$

$y_i$ is the true response value of the $i$-th sample; $\hat{y}_i$ is the model prediction value; $l(\cdot)$ is the loss function. Squared error is used for regression tasks, and logarithmic loss is used for classification tasks. $f_k$ represents the $k$-th decision tree; $\Omega(f_k) = \gamma T + \frac{1}{2}\lambda\|w\|^2$ controls the number of leaf nodes $T$ and the complexity of weights $w$ in each tree; $\gamma$ and $\lambda$ are the regularization parameters. The model ensemble strategy uses gradient boosting, fitting the negative gradient direction of the residuals in each iteration to gradually optimize the overall performance.

The hyperparameter configuration is determined after multiple rounds of tuning. The maximum tree depth is set to 8 to limit the branch levels and prevent excessive subdivision. The learning rate is fixed at 0.05 to enhance iterative stability. The column sampling rate is set to 0.7, using only a subset of features in each split to improve generalization ability. The training process implements five-fold cross-validation, maintains consistency in data distribution between groups, and uses random seed locking to ensure reproducibility. The final model retains the entire

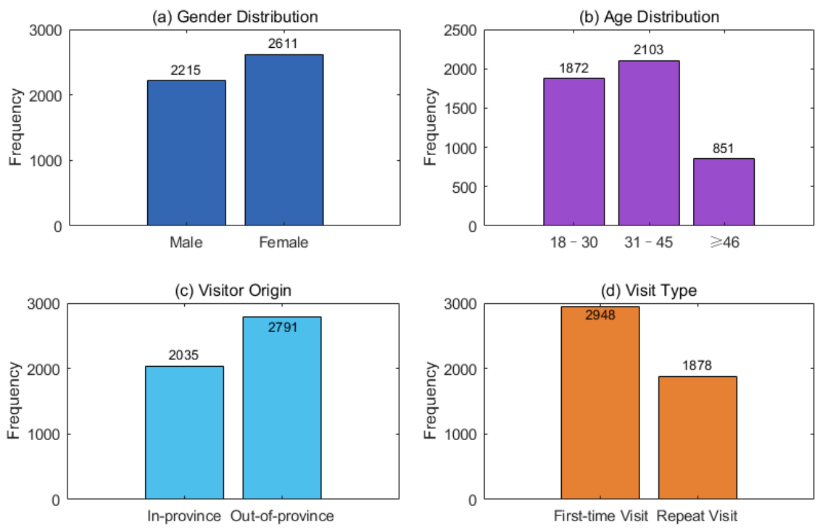


**FIGURE 1.** Demographic characteristics of the sample (N = 4,826)

set of weak learners, and the output structure is used for subsequent individual-level contribution analysis to support fine-grained decomposition of the driving path. Figure 2 presents the professional architecture of the XGBoost model in identifying the driving effects of tourism marketing. The 13-dimensional input features cover six types of marketing activities and seven psychological motivations, which are standardized and then fed in parallel into multiple decision trees with a depth not exceeding 8. Each tree outputs leaf node weights, and a regularization mechanism is used to control complexity. The predictions from all trees are integrated additively to form a unified output, which is then distributed by the routing module according to behavioral intention type: spending amount follows a regression path, while revisiting and recommendation intentions are converted into high-intention binary classification outputs. The overall design focuses on interpretable modeling of nonlinear driving paths, supporting the causal link analysis from marketing intervention to psychological response to behavioral decision-making.

### D. APPLYING SHAP VALUES TO ANALYZE THE CAUSAL PATH OF MARKETING-MOTIVATION-BEHAVIOR

The fine-grained decomposition of the driving path relies on the TreeSHAP algorithm to achieve interpretability transformation of feature contributions. This method, based on the Shapley value in cooperative game theory, assigns a unique marginal effect measure to each input variable, reflecting its actual influence direction and strength in the prediction results of a specific sample. For the trained XGBoost model, the SHAP values of the 13 input features are calculated for each of the 4,826 valid observations, forming an attribution matrix at the individual level. Positive or negative values indicate promoting or inhibiting effects, and the absolute value reflects the degree of contribution, preserving the local interpretability under the original nonlinear relationship.

Path analysis focuses on the mediating mechanism by which marketing activities are transmitted from psychological motivation to behavioral intention. It extracts the SHAP value sequences of six marketing variables and seven motivational dimensions, and uses conditional expected value estimation to assess the trend of SHAP value fluctuations of a specific motivation caused by changes in a particular marketing characteristic, while keeping other covariate values constant. A path weighting index is constructed.

$$W_{m\to k\to b} = E[\phi_b^y \mid \phi_m^x, \phi_k^z] \tag{2}$$

$\phi_m^x$ represents the SHAP contribution of the $m$-th marketing activity to the input $x$; $\phi_k^z$ represents the SHAP attribution value of the $k$-th psychological motivation to the latent variable $z$; $\phi_b^y$ represents the response of the behavioral intention output $y$. The combined expectation of these three factors characterizes the strength of the chain association from stimulus to internal state to overt behavior. High-dimensional interactive influences are naturally incorporated into the calculation process without the need for pre-defined function forms.

It is important to emphasize that the SHAP product in this study reflects the joint strength of the predictive contributions of the three-stage variables, used to identify potentially high-impact attribution paths, not a formal test of causal mediation effects. Therefore, the interpretation should be limited to the level of "attribution path strength."

### E. HETEROGENEITY TESTS CONDUCTED BY GROUPING TOURISTS BY ATTRIBUTES AND SCENIC AREA TYPE

Heterogeneity tests employ a stratified grouping strategy to reveal the differentiated manifestations of driving effects across different populations and contexts. The sample is

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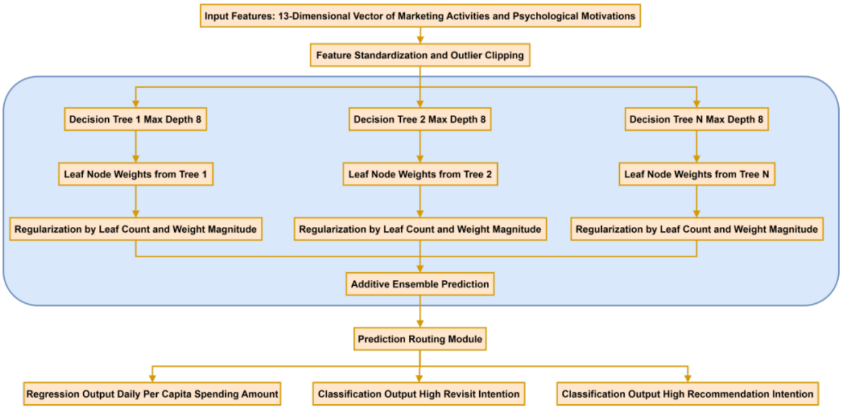


**FIGURE 2.** XGBoost model architecture

divided into multiple subsets based on demographic characteristics and spatial attributes. Age is categorized into 18–30 years, 31–45 years, and $\geq$46 years. Visit type is differentiated into first-time and repeat visitors based on past visit records. Origin is defined by administrative boundaries as local and out-of-province tourists. Scenic spot type is categorized into natural scenery, historical and cultural sites, and urban leisure sites. All grouping criteria are independent and supported cross-comparison.

Within each group, the SHAP path weights are recalculated independently, preserving the original model structure. The activation intensity of each marketing campaign on psychological motivation and its transmission efficiency to behavioral intentions are reassessed on the subsamples. The core indicators are the standardized average SHAP contribution value and the mediation path coefficient, reflecting the magnitude of the interaction between variables within a specific group. Cross-group comparisons use a weighted difference measure.

$$\Delta_{g,g'} = \frac{1}{N}\sum_{i=1}^{N}\left|\phi_i^{(g)} - \phi_i^{(g')}\right| \tag{3}$$

$\phi_i^{(g)}$ represents the average SHAP value of the $i$-th feature in the group $g$, and $\phi_i^{(g')}$ represents the corresponding value in the reference group or other comparison groups. The mean of the absolute values of the differences quantifies the overall deviation of the driving patterns between the two groups. High difference values indicate significant context dependence.

## III. QUANTITATIVE ASSESSMENT OF THE DRIVING ROLE OF TOURISM MARKETING

### A. HORIZONTAL COMPARISON AND VALIDATION OF MODEL PREDICTION PERFORMANCE

Using RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), R2 (for regression tasks), AUC (Area Under Curve), and F1-score (for classification tasks) as evaluation metrics, and under the same data partitioning and hyperparameter tuning strategies, the proposed XGBoost-SHAP framework is compared with five mainstream models: RF (Random Forest), LightGBM, CatBoost (Categorical Boosting), SVM (Support Vector Machine), and MLP (Multilayer Perceptron), to verify its effectiveness in modeling complex nonlinear relationships.

Figure 3 presents a performance comparison of six models under five evaluation metrics. The horizontal axis represents the model name, and the vertical axis corresponds to the metric value. XGBoost-SHAP has the lowest RMSE (0.82±0.012) and MAE (0.63±0.009) values, and the highest R2 (0.76±0.008), reflecting its smallest fitting error for consumption amount and the largest explained variance. It also ranks first in AUC (0.89±0.007) and F1-score (0.84±0.008), indicating optimal accuracy and category balance in identifying high-intent tourists. The small error margin reflects the high stability of the results under five-fold cross-validation. The performance advantage stems from the model's adaptive ability to capture nonlinear interactions and threshold effects of features, especially fitting the conditional dependence between marketing stimuli and psychological motivations. Other models are limited by structural constraints or sensitivity to sparse high-dimensional features, and perform worse in modeling complex behavioral paths. The consistency of all indicators points to the same conclusion, eliminating the interference of randomness from a single indicator and enhancing the applicability and robustness of XGBoost-SHAP in tourism behavior-driven modeling.

### B. DIFFERENTIATION OF MARKETING CAMPAIGN TYPES IN DRIVING BEHAVIORAL INTENTIONS

Driving force strength is assessed by the within-group mean absolute SHAP value, reflecting the average marginal impact of each marketing campaign type on behavioral intentions. The sample is split into four subgroups by visit frequency (first-time vs. repeat) and origin (within vs. outside province). For each subgroup, mean SHAP values—retaining sign to indicate facilitation or inhibition—are computed across six campaign types and three behavioral intentions. Strategy context dependence is identified by

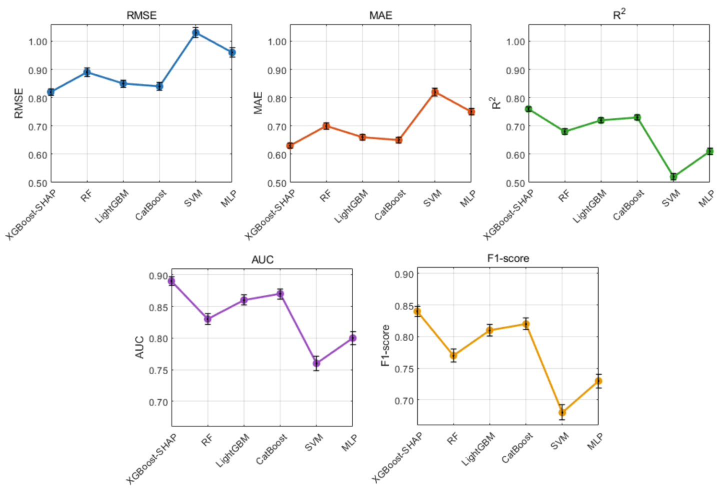


**FIGURE 3.** Comparison of model prediction performance

comparing intensity rankings of the same campaign across subgroups. All results derive from aggregated individual-level SHAP attributions, ensuring fine-grained group inference.

Table 1 suggests a systematic change in the efficiency of marketing campaigns according to tourist identity structure. First-time visitors from out of the province matter most to short video exposure, with the strength of the recommendation intention drive being 0.34, which is much greater than other promotion strategies. This indicates that once in an unfamiliar place, they depend on highly immersive and visual content to form initial cognitive and emotional connections with the destination. Provincial returnees are also very receptive to festival programs, with a festival intention strength of 0.30, meaning that local returnees are more inclined to value physical participation and experiencing rituals of cultural. KOL collaborations tend to be more effective for first-time visitors but their effectiveness decreases slightly for repeat visitors; the effect of coupons is slightly higher for first-time visitors from within the province suggesting that price sensitivity is moderated by location and familiarity. It can be found that the contribution of offline advertising is relatively small overall, which suggests a passive exposure to information most likely does not trigger a deep desire to act. The observed data pattern confirms that marketing efficiency is not unconditionally generalizable but firmly situated in the tourists' stage of cognition and geographical psychological distance. The data demonstrates that short videos have the strongest recommendation intention drive for first-time visitors from outside the province (0.34), while festival activities have the most significant revisit intention drive for repeat visitors (0.31).

**TABLE 1.** Analysis of the driving effect of marketing activities

| Marketing Activity Type | Out-of-Province First- Time Visitors (Recommendation Intention) | In-Province First-Time Visitors (Recommendation Intention) | Out-of-Province Repeat Visitors (Revisit Intention) | In-Province Repeat Visitors (Revisit Intention) |
|---|---|---|---|---|
| Short Video Exposure Frequency | 0.34 | 0.28 | 0.22 | 0.19 |
| KOL Collaboration Count | 0.29 | 0.25 | 0.2 | 0.18 |
| Festival Event Frequency | 0.18 | 0.2 | 0.31 | 0.30 |
| Social Media Engagement Rate | 0.24 | 0.22 | 0.25 | 0.23 |
| Offline Ad Coverage Density | 0.15 | 0.17 | 0.19 | 0.21 |
| Coupon Distribution Intensity | 0.2 | 0.23 | 0.17 | 0.16 |

Note: Ad is an abbreviation for Advertisement.

### *C. MEDIATING ROLE OF PSYCHOLOGICAL MOTIVATION IN THE DRIVING LINK*

The mediation effect is assessed using the SHAP product method: for each respondent, the element-wise product of SHAP values from any marketing and motivational feature is computed, and then averaged within each age group (18–30, 31–45, $\geq$46) to form a "marketing-motivation" mediation strength matrix. Positive means co-directional influence; larger values denote stronger mediation. Analyzing 42 paths across six marketing types and seven motivations, the top three motivational dimensions with highest mediation per age group are identified. All calculations use original SHAP values, avoiding linear assumptions or predefined paths to preserve true non-linear mediation structure.

Table 2 displays a life stage variation that reveals psychological motivation parallelly functions as a mediator. In the 18–30 age group, the SHAP product path strength corresponding to social identity is the highest (0.20), indicating that young travelers rationalize their travel behavior through the acquisition of social capital; marketing messages that promote identity expression or social group belonging notoriously convert into behavioral intentions. Motivations for the 31–45 age group are also relatively evenly split between a cognitive and a family-related caring dual focus, with cultural exploration (0.19) and family companionship (0.18) given almost equal importance. In the ≥46 age group, the escapism path strength is the highest (0.22), relaxation/stress reduction at 0.20) signifying that mature travelers tend to use destinations more as mental wedges from everyday stress and that they are particularly responsive to advertising linking travel to peace, healing and/or nostalgic storytelling. Motivational rank differences are not mere random variation but are influenced by an interplay of cost-benefit analysis, social role pressure, and self-concept expansion. In the 18-30 age group, social identity becomes the strongest mediating effect; while in the ≥46 age group, escapism becomes the strongest mediating effect (0.22).

**TABLE 2.** Mediating role of psychological motivation

| Psychological Motivation | Age 18–30 (Mean Product) | Age 31–45 (Mean Product) | Age ≥46 (Mean Product) |
|---|---|---|---|
| Social Recognition | 0.20 | 0.15 | 0.1 |
| Novelty Seeking | 0.18 | 0.17 | 0.12 |
| Cultural Exploration | 0.16 | 0.19 | 0.14 |
| Escape from Reality | 0.11 | 0.13 | 0.22 |
| Relax and de-Stress | 0.13 | 0.16 | 0.2 |
| Self-Actualization | 0.12 | 0.14 | 0.13 |
| Family Companionship | 0.09 | 0.18 | 0.17 |

### *D. STABILITY OF DRIVING EFFECTS AMONG SCENIC AREA TYPES*

The stability assessment of driving paths is quantified based on the dispersion of the SHAP contribution value in five-fold cross-validation. For each "marketing-motivation-behavior" ternary path, the mean of its SHAP product is calculated in each cross-validation fold, resulting in five repeated observations. The coefficient of variation (CV) is obtained by dividing the standard deviation of the sequence by its mean, measuring the robustness of path strength under data perturbation; a lower CV indicates a more stable mechanism. The samples are divided into three groups according to scenic area type: natural scenery, historical and cultural sites, and urban leisure sites. The CV of all potential paths within each group is calculated, and the dominant path with the smallest CV in each scenic area type is selected.

Table 3 depicts the coefficient of variation (CV) reflecting the robustness of the driving path under data perturbation; the lower the value, the more reliable the mechanism. In historical and cultural scenic areas, the CV for the path of KOL collaboration driving revisit intention through cultural exploration is only 0.02, indicating that authoritative narratives and in-depth content continuously stimulate cognitive resonance in this type of scenario, forming a stable logic for repeat visits. Urban leisure scenic areas exhibit a strong experience-oriented approach, with the CV for the path of short videos driving consumption through the motivation of seeking novelty being 0.04, aligning with urban tourists' preference for instant stimulation and novelty check-ins. Natural scenic areas have relatively low path stability, suggesting that their driving force is more dependent on environmental context and individual mood, and is easily affected by external factors. The core path differences among the three types of destinations are rooted in their symbolic meaning and functional positioning: cultural venues emphasize the inheritance of meaning; urban spaces focus on sensory renewal; natural areas tend towards emotional regulation. Data confirms that the KOL collaboration quantity-cultural exploration-revisit path is the most stable in historical and cultural scenic areas (CV=0.02), while the short video exposure frequency-seeking novelty-consumption path has the highest stability in urban leisure scenic areas (CV=0.04). It should be emphasized that while the dominant paths identified in Table 3 exhibit high stability within this study's sample, their generalization should be limited to scenic areas with similar functional attributes and cultural contexts. For example, the robust performance of the 'KOL collaboration → cultural exploration' path in historical and cultural scenic areas may not be applicable to other cultural sites lacking narrative depth or authoritative symbolic systems. Strategy transfer needs to be calibrated in conjunction with the local content ecosystem and tourist cognitive schemas.

**TABLE 3.** Stability of driving effects among scenic area types

| Destination Type | Dominant Driving Path | CV |
|---|---|---|
| Natural Scenery | Short Video Exposure Frequency → Relax and de-Stress → Revisit Intention | 0.12 |
| Historical-Cultural | KOL Collaboration Count → Cultural Exploration → Revisit Intention | 0.02 |
| Urban-Leisure | Short Video Exposure Frequency → Novelty Seeking → Daily Spending | 0.04 |
| Natural Scenery | Festival Event Frequency → Escape from Reality → Recommendation | 0.13 |
| Historical-Cultural | Offline Ad Coverage Density → Family Companionship → Recommendation | 0.11 |
| Urban-Leisure | Social Media Engagement Rate → Social Recognition → Recommendation | 0.1 |

## IV. CONCLUSION

In this paper, the XGBoost-SHAP-based attribution model is developed to expose the nonlinear process of tourism marketing on tourists' psychology and behavior. This powerful, explanatory model is highly transferable, offering a crucial analytical tool for the industry to accurately map the complex, nonlinear impacts of its branding efforts on consumer identity, emotion, and subsequent purchasing decisions. Effectiveness of tourism marketing activities is not universal, and the effectiveness is embedded in a multidimensional environment of the tourist's identity characteristics, the life cycle stage, and the tourism destination type. Social identity is more influential among the younger cohorts whereas older tourists are more influenced by escapist routes. First-time out-of-province visitors are more influenced by digital products, and repeat visitors are more influenced by physical festival experiences. Historic and cultural venues depend on authoritative narratives, urban leisure spaces rely on new encounters for conversion. Psychological motivation serves as a critical mediator and its manifestation dynamically changes across different ages and contexts. This framework surpasses linear assumptions and enables micro-foundations via the analysis from variable association to the contextualized causal chain, offering actionable attribution evidence and decision support for tailored tourism marketing strategies. Critically, this capability provides a powerful, transferable model that allows the industry to move beyond surface trends, using the causal chain analysis to inform precise product development and highly individualized marketing strategies in the global consumer market.

## AUTHOR CONTRIBUTIONS

Yutong Yang designed, collected and analyzed the data, and drafted the manuscript. Yutong Yang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Yutong Yang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

## CONFLICTS OF INTEREST

The author declares no conflict of interest.

## FUNDING

This research received no external funding.

## HUMAN RESEARCH SUBJECTS

This study was approved by the Ethics Committee of Macau University of Science and Technology, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

## ACKNOWLEDGEMENTS

Not applicable.

## REFERENCES

[1] J. Wang and V. Butkouskaya, "Sustainable marketing activities, event image, perceived value and tourists' behavioral intentions in the sports tourism," Journal of Economics, Finance and Administrative Science, vol. 28, no. 55, pp. 60-78, 2023, doi: 10.1108/JEFAS-09-2022-0219.

[2] W. K. S. Leung, M. K. Chang, M. L. Cheung, and S. Shi, "VR tourism experiences and tourist behavior intention in COVID-19: An experience economy and mood management perspective," Information Technology & People, vol. 36, no. 3, pp. 1095-1125, 2023, doi: 10.1108/ITP-06-2021-0423.

[3] S. Hashemi, H. J. Mohammed, S. Kiumarsi, D. M. H. Kee, and B. B. Anarestani, "Destinations food image and food neophobia on behavioral intentions: Culinary tourist behavior in Malaysia," Journal of International Food & Agribusiness Marketing, vol. 35, no. 1, pp. 66-87, 2023, doi: 10.1080/08974438.2021.1943101.

[4] Z. Ghaderi, M. J. Mahdavizadeh, M. Rajabi, and C. M. Hall, "Does storytelling affect destination image, destination personality, and tourists' behavioural intention?," Anatolia, vol. 35, no. 2, pp. 313-325, 2024, doi: 10.1080/13032917.2023.2191250.

[5] M. K. Hasan, R. Ray, and N. M. Neela, "Tourists' behavioural intention in coastal tourism settings: Examining the mediating role of attitude to behaviour," Tourism Planning & Development, vol. 20, no. 6, pp. 955-972, 2023, doi: 10.1080/21568316.2021.2001035.

[6] S. Seyfi, S. M. Rasoolimanesh, A. Vafaei-Zadeh, and K. Esfandiar, "Can tourist engagement enhance tourist behavioural intentions? A combination of PLS-SEM and fsQCA approaches," Tourism Recreation Research, vol. 49, no. 1, pp. 63-74, 2024, doi: 10.1080/02508281.2021.1981092.

[7] T. B. Luong, "The role of satisfaction in the relationship between destination image and behavioral intention: A case study of Vietnamese visitors to Thailand," Journal of Policy Research in Tourism, Leisure and Events, vol. 17, no. 2, pp. 494-516, 2025, doi: 10.1080/19407963.2023.2231475.

[8] T. Hansen, S. Olk, and T. U. Thomsen, "A meta-analysis of sustainable tourist behavioral intention and the moderating effects of national culture," Journal of Sustainable Tourism, vol. 32, no. 5, pp. 883-903, 2024, doi: 10.1080/09669582.2023.2186825.

[9] T. B. Luong, "Eco-destination image, place attachment, and behavioral intention: The moderating role of eco-travel motivation," Journal of Ecotourism, vol. 23, no. 4, pp. 631-656, 2024, doi: 10.1080/14724049.2023.2286886.

[10] X. Li and C. Wang, "Understanding the relationship between tourists' perceptions of the authenticity of traditional village cultural landscapes and behavioural intentions, mediated by memorable tourism experiences and place attachment," Asia Pacific Journal of Tourism Research, vol. 28, no. 3, pp. 254-273, 2023, doi: 10.1080/10941665.2023.2217959.

[11] G. Roy, B. Datta, S. Mukherjee, A. Eckert, and S. K. Dixit, "How online travel reviews sources affect travelers' behavioral intentions? Analysis with source credibility theory," Tourism Planning & Development, vol. 21, no. 3, pp. 299-329, 2024, doi: 10.1080/21568316.2023.2229296.

[12] R. Jokom, D. C. Widjaja, M. Kristanti, and S. Wijaya, "Culinary and destination experiences on behavioral intentions: An insight into local Indonesian food," Journal of Foodservice Business Research, vol. 28, no. 1, pp. 145-162, 2025, doi: 10.1080/15378020.2023.2229574.

[13] F. Jorge, N. Losada, and M. S. Teixeira, "Behavioural intentions through virtual reality from a destination image perspective," Journal of Place Management and Development, vol. 16, no. 3, pp. 347-366, 2023, doi: 10.1108/JPMD-02-2022-0016.

[14] J. Wang, Q. He, L. Qian, and G. Wang, "From ruins to heritage tourism sites: Exploring tourists' perceptions, evaluations and behavioral intentions toward natural disaster sites," Tourism Review, vol. 78, no. 3, pp. 949-965, 2023, doi: 10.1108/TR-08-2022-0372.

[15] Y. J. Lee, "Destination fascination, well-being, and the reasonable person model of behavioural intention in heritage tourism," Current Issues in Tourism, vol. 27, no. 2, pp. 288-304, 2024, doi: 10.1080/13683500.2023.2178395.

[16] N. Devkota, K. Gajdka, R. Siwakoti, M. Klímová, and K. Dhakal, "Promoting sustainable tourist behavior through promotional marketing," Journal of Tourism and Services, vol. 14, no. 26, pp. 219-241, 2023, doi: 10.29036/jots.v14i26.512.

[17] E. Sthapit, P. Björk, and S. Piramanayagam, "Domestic tourists and local food consumption: Motivations, positive emotions and savouring processes," Annals of Leisure Research, vol. 26, no. 2, pp. 316-337, 2023, doi: 10.1080/11745398.2021.1993287.

[18] Y. Gao, Z. Zhao, Y. Ma, and Y. Li, "A rational-affective-moral factor model for determining tourists' proenvironmental behaviour," Current Issues in Tourism, vol. 26, no. 13, pp. 2145-2163, 2023, doi: 10.1080/13683500.2022.2078687.

[19] M. H. Dewantara, S. Gardiner, and X. Jin, “Travel vlog ecosystem in tourism digital marketing evolution: A narrative literature review,” Current Issues in Tourism, vol. 26, no. 19, pp. 3125-3139, 2023, doi: 10.1080/13683500.2022.2136568.

[20] Á. Rodrigues, S. M. C. Loureiro, M. Lins de Moraes, and R. G. Pereira, “Memorable tourism experience in the context of astrotourism,” Anatolia, vol. 34, no. 2, pp. 235-247, 2023, doi: 10.1080/13032917.2021.2015695.

[21] Z. Xu, G. Yang, L. Wang, L. Guo, and Z. Shi, “How does destination psychological ownership affect tourists’ proenvironmental behaviors? A moderated mediation analysis,” Journal of Sustainable Tourism, vol. 31, no. 6, pp. 1394-1412, 2023, doi: 10.1080/09669582.2022.2049282.

[22] S. D. Elgarhy, W. M. A. N. Abdel Rahieem, and M. Abdulmawla, “Influences of gamification on repurchase intention and intrinsic motivations in Egyptian hotels and travel agencies: The mediating role of customer engagement,” Journal of Quality Assurance in Hospitality & Tourism, vol. 25, no. 2, pp. 397-419, 2024, doi: 10.1080/1528008X.2023.2194705.

[23] G. Qiao, H. Chen, G. Li, H. Liu, and X. Wang, “The role of filial piety in filial tourism: An intergenerational analysis of decision-making,” Asia Pacific Journal of Tourism Research, vol. 29, no. 8, pp. 1017-1031, 2024, doi: 10.1080/10941665.2024.2362199.

[24] N. Soltani Nejad, R. Rastegar, and M. Jahanshahi, “Tourist engagement with mobile apps of E-leisure: A combined model of self-determination theory and technology acceptance model,” Tourism Recreation Research, vol. 49, no. 4, pp. 714-725, 2024, doi: 10.1080/02508281.2022.2100194.

[25] S. M. Rasoolimanesh and S. Lu, “Enhancing emotional responses of tourists in cultural heritage tourism: The case of Pingyao, China,” Journal of Heritage Tourism, vol. 19, no. 1, pp. 91-110, 2024, doi: 10.1080/1743873X.2023.2254420.

[26] A. Douglas, G. Hoogendoorn, and G. Richards, “Activities as the critical link between motivation and destination choice in cultural tourism,” Journal of Hospitality and Tourism Insights, vol. 7, no. 1, pp. 249-271, 2024, doi: 10.1108/JHTI-09-2022-0442.

[27] P. M. B. Nguyen, X. L. Pham, and G. N. T. Truong, “The influence of source credibility and inspiration on tourists’ travel planning through travel vlogs,” Journal of Travel Research, vol. 64, no. 1, pp. 222-237, 2025, doi: 10.1177/00472875231206538.

[28] N. T. K. Chi and H. Pham, “The moderating role of eco-destination image in the travel motivations and ecotourism intention nexus,” Journal of Tourism Futures, vol. 10, no. 2, pp. 317-333, 2024, doi: 10.1108/JTF-01-2022-0014.

[29] I. Šagovnović and S. Kovačić, “Predicting travel motivation with personality and personal values–the roles of big five plus honesty/humility personality traits and Kahle’s values,” International Journal of Hospitality & Tourism Administration, vol. 24, no. 4, pp. 614-643, 2023, doi: 10.1080/15256480.2021.2025189.

[30] R. Buckley, “Tourism and mental health: Foundations, frameworks, and futures,” Journal of Travel Research, vol. 62, no. 1, pp. 3-20, 2023, doi: 10.1177/00472875221087669.

[31] A. Galati, R. Testa, G. Schifani, and G. Migliore, “Tourists’ motivation toward culinary destination choice: Targeting Italian tourists,” Journal of Foodservice Business Research, vol. 26, no. 4, pp. 647-668, 2023, doi: 10.1080/15378020.2021.1948295.

[32] S. Hosseini, R. Cortes-Macías, and F. Almeida-García, “Extending the memorable tourism experience construct: An investigation of tourists’ memorable dark experiences,” Journal of Vacation Marketing, vol. 30, no. 1, pp. 21-44, 2024, doi: 10.1177/13567667221113078.

[33] E. Sthapit, P. Björk, and D. N. Coudounaris, “Towards a better understanding of memorable wellness tourism experience,” International Journal of Spa and Wellness, vol. 6, no. 1, pp. 1-27, 2023, doi: 10.1080/24721735.2022.2136120.

[34] U. Akram, R. Lavuri, M. Bilal, I. Hameed, and J. Byun, “Exploring the roles of green marketing tools and green motives on green purchase intention in sustainable tourism destinations: A cross-cultural study,” Journal of Travel & Tourism Marketing, vol. 41, no. 4, pp. 453-471, 2024, doi: 10.1080/10548408.2023.2293022.

[35] E. Sthapit, P. Björk, D. N. Coudounaris, and J. Jiménez-Barreto, “Memorable Halal tourism experience and its effects on place attachment,” International Journal of Hospitality & Tourism Administration, vol. 25, no. 3, pp. 575-601, 2024, doi: 10.1080/15256480.2022.2135666.