An Explainable Machine Learning Framework for Predicting Travel Intention in Virtual Tourism: Evidence from Da Nang, Vietnam

Jenny Morales Brito, Fabián Silva-Aravena, and Miguel Morales-Beltrán

Abstract—**Virtual tourism is transforming the way users explore and evaluate travel destinations, yet accurately predicting the intention to visit after engaging in virtual experiences remains a challenge. Existing approaches often lack predictive accuracy and interpretability, limiting their application in tourism decision making. To address this, we develop a machine learning framework that integrates explainable artificial intelligence (XAI) to predict the intention to travel after experience with high accuracy and transparency. We implement eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and Multilayer Perceptron (MLP), applying cross-validation for robustness and Optuna-based Bayesian optimization to maximize model performance. To ensure interpretability, we employ SHapley Additive Explanations (SHAP). Our results show that XGBoost outperforms all models, achieving an accuracy of 93.21% and a cross-validation accuracy of 94.08%, validating its robustness. SHAP analysis reveals that psychological engagement, such as emotional involvement, enjoyment, and immersive flow states, are key drivers of travel intention, with individual SHAP values further elucidating user-specific decision patterns. These findings align with consumer behavior theories, reinforcing the role of psychological and experiential factors in travel decisions. Our study presents a highly accurate, interpretable, and scalable predictive model that advances virtual tourism analytics, providing actionable insights for destination marketing and strategic tourism management. Future research should explore real-time user interactions, adaptive learning techniques, and external variables (social sentiment, economic conditions) to improve predictive accuracy and practical applicability.**

Link to graphical and video abstracts, and to code:
https://latamt.ieeer9.org/index.php/transactions/article/view/10756

Index Terms—**Travel Intention Prediction, Tourist eXperience, Virtual Reality in Tourism, XGBoost and Neural Networks, Explainable Artificial Intelligence, Machine Learning in Tourism.**

I. Introduction

THE emergence of virtual reality technology has changed the way travelers research places before deciding where to go [1]. Virtual tourism experiences refer to digitally mediated environments that allow users to explore destinations remotely using immersive technologies and interactive multimedia content. These experiences can include 360° virtual tours, virtual reality-based destination simulations, augmented reality tourism applications, virtual museum visits, interactive cultural heritage platforms, and metaverse-based tourism environments, where users can evaluate destinations before planning their trips thanks to the immersive digital experience offered by this technology [2], [3]. Currently, there are some limited approaches to forecasting travel intent based on digital interactions, although virtual experiences are becoming more and more popular on tourism platforms [4]. The design of successful promotional campaigns and the transformation of virtual trips into real travel requires an understanding of the aspects that ultimately influence the decision [1], [5].

In the literature, we identified a number of methods for modeling travel intent. Conventional techniques such as structural equation modeling and logistic regression have found correlations between user perceptions, travel decisions, and demographic characteristics [6], [7], [9]. However, these models have limitations when it comes to using large amounts of data and capturing nonlinear relationships. Predictive precision has recently increased with the use of neural networks and boost methods. However, there are still issues with model interpretability and choosing the best hyperparameters, which prevent wider use in the real world [10], [11].

The ability to predict travel intention has become increasingly important for tourism stakeholders operating in highly competitive and digitally mediated environments. Accurate prediction of whether users exposed to virtual tourism experiences are likely to convert into actual visitors provides substantial strategic value for destination managers, tourism agencies, and digital marketing platforms [12], [13].

The growing interest in digital experiences within the tourism industry underscores the need for reliable predictive models [14], [15]. Understanding what motivates users to travel after a virtual experience enables personalized marketing campaigns and efficient allocation of resources to tourist destinations. Despite advances in artificial intelligence models, few studies have addressed the explainability of predictions, which is crucial for industry stakeholders to understand the factors driving tourism decision-making processes. Predicting travel intentions after virtual tourism experiences is particularly relevant in the current post-pandemic context, where digital engagement plays a central role in travel decision making.

In a highly competitive and digitally driven tourism market, understanding the determinants of virtual to real travel conversion supports data-informed decisions and maximizes return on investment for destinations. Therefore, developing

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interpretable and scalable models to anticipate user behavior is not only a methodological challenge but a strategic necessity.

This study develops an optimized predictive model to estimate travel intent after a virtual tourism experience. We implement XGBoost, LightGBM, and MLP, incorporating advanced data normalization techniques and Bayesian hyperparameter optimization to enhance model performance. In addition, we apply SHAP to interpret the contribution of each variable to the final prediction. This research contributes to the explainability of the model, offering a clear understanding of the key factors that influence travel decisions of users. The main contributions of this work are summarized as follows:

1- We develop and compare three advanced machine learning models (XGBoost, LightGBM, and MLP) to predict travel intention in a virtual tourism context.

2- We incorporate Bayesian hyperparameter optimization using Optuna to improve predictive accuracy, robustness, and model generalization.

3- We integrate SHAP-based explainability to provide transparent interpretation of model predictions and identify the most influential psychological and experiential factors affecting travel intention.

4- We demonstrate that emotional engagement, enjoyment, and immersive flow are key determinants of virtual-to-real travel conversion, providing actionable insights for tourism stakeholders and destination marketing strategies.

5- We provide an interpretable and scalable predictive framework that contributes to the advancement of data-driven tourism analytics and explainable artificial intelligence applications in tourism research.

This paper is structured as follows. Section 2 presents a review of the literature on the prediction of travel intentions using artificial intelligence techniques. Section 3 describes the methodology, including data pre-processing, model selection, and hyperparameter optimization. Section 4 presents the results obtained and compares them with previous studies. Section 5 discusses the findings and describes future research directions. Finally, Section 6 highlights the conclusions and practical applications of the study.

II. Literature Review

The prediction of travel intent has drawn more attention in tourism research, particularly when decision making is influenced by digital platforms [16]. Some researchers have looked at user demographics, destination perceptions, and travel behavior using statistical models such as logistic regression and structural equation modeling [6], [9]. Although these approaches yielded insightful results, they had trouble capturing complex relationships and non-linear connections. The increasing accessibility to huge datasets has brought attention to the demand for sophisticated machine learning methods that can analyze multidimensional data while preserving interpretability.

Recent studies on explainable AI in accessibility and decision support systems emphasize the growing need for interpretable models in user-facing applications [17], [18]. However, despite these advances, there is a noticeable lack of research applying explainable machine learning techniques to virtual tourism contexts. We aim to address this gap by integrating SHAP-based explainability with predictive models to improve transparency and user trust in travel intention forecasting.

In the tourism industry, machine learning algorithms have greatly improved predictive analytics. When it comes to modeling travel intent, techniques such as random forests, support vector machines, and deep learning have performed better than conventional approaches [19], [20]. Online travel data has been used for sentiment analysis and behavioral prediction using deep learning models, especially recurrent and convolutional networks [21], [22].

In structured data problems, gradient boost algorithms, such as XGBoost and LightGBM, have been proven to perform very well by combining high accuracy and efficiency [27]. By iteratively improving weak learners, these models reduce bias and variance in classification tasks.

The need for clear and understandable models is highlighted by the growing use of artificial intelligence (AI) in the travel industry [28], [29]. In order to make machine learning models more responsible and perceptive, XAI techniques have attracted increased attention [30], [31]. Among these, SHAP provides a feature importance attribution technique with a mathematical foundation. SHAP is perfect for understanding consumer decision making because, in contrast to heuristic-based approaches, it offers consistent and equitable contributions for every predictor. Its use in tourism is still unexplored, despite its efficacy in fields such as healthcare and banking [32].

Despite the growing adoption of machine learning techniques in tourism research, several important limitations remain in the current literature. First, many previous studies primarily focus on predictive performance without incorporating explainability mechanisms capable of clarifying how individual variables influence travel intention predictions. Second, although advanced algorithms such as neural networks and boosting models have demonstrated promising results, few studies combine predictive optimization with transparent interpretation frameworks suitable for supporting managerial decision-making. Third, existing research on virtual tourism frequently emphasizes user experience analysis rather than predictive modeling of virtual-to-real travel conversion behavior.

In contrast, our study integrates optimized machine learning models with SHAP-based explainable artificial intelligence to simultaneously achieve high predictive performance and interpretability. Additionally, we incorporate Bayesian hyperparameter optimization to improve robustness and generalization while providing individualized explanations of user travel intention. These methodological and practical differences position our framework as a novel contribution to explainable tourism analytics and data-driven tourism management [12], [33]–[35]. Please see Table I.

III. Methodology

In this section, we outline our methodological framework for predicting the intention to travel to Da Nang, Vietnam,

TABLE I
COMPARATIVE ANALYSIS OF PREVIOUS VIRTUAL TOURISM STUDIES AND THE PROPOSED EXPLAINABLE MACHINE LEARNING FRAMEWORK FOR TRAVEL INTENTION PREDICTION

Studies on Virtual Tourism	**Contribution to the Literature**
Previous literature on virtual tourism	Previous studies have primarily relied on traditional theoretical frameworks such as TAM, PADM, and SOR models to explain tourist behavior in virtual environments [6]–[35].
Proposed study	Unlike previous studies, the proposed framework integrates multiple machine learning models and explainable artificial intelligence (XAI) techniques, specifically SHAP, allowing not only the prediction of tourist behavior but also the transparent interpretation of the variables that explain users' travel intention.

following virtual tourism experiences. We integrate machine learning, hyperparameter optimization, and explainability to enhance predictive accuracy and interpretability. Specifically, we evaluate the XGBoost, LightGBM, and MLP models, refining their performance through cross-validation and Bayesian optimization. To ensure transparency, we employ SHAP analysis to identify the most influential factors driving travel intent (please see Fig. 1 in the section Annexes). This approach not only improves the precision of the model, but also provides actionable insights into user engagement, supporting data-driven decision-making in virtual tourism.

A. Data Set

We used a publicly accessible dataset available at https://data.mendeley.com/datasets/2tg7ffdr56/1. It contains anonymized survey responses from individuals who participated in a virtual tourism experience in Da Nang, Vietnam. Since no personally identifiable information is included, ethics approval was not required. In [36], the authors conducted a study related to the previous virtual reality experience with the intention of potential tourists to visit Da Nang in Vietnam. The data collection instrument used and its description, detailing the construct, the measurement code, and the item declaration (see [36]). It is essential to indicate that the scale associated with these items is 1 to 5, where 1 is "strongly disagree" and 5 is "strongly agree". The questionnaire also includes sociodemographic questions: Sex (female; male); Marital status (single; married; other); Income (less than 5 million; between 5 and less than 10 million; between 10 and less than 20 million; greater than or equal to 20 million); Age group (between 18 and 30 years; between 31 and 55 years; over 55 years); Number of trips (domestic and international) this year (0; between 1 and 3; between 4 and 6; more than 6); and Have you ever heard of virtual reality? (yes; no) [36] (please see, Table II.

We encoded the responses for the analysis as follows: Gender [1 = Male, 2 = Female], where the final dataset used for the analysis consisted of 359 observations collected from participants exposed to virtual tourism experiences related to

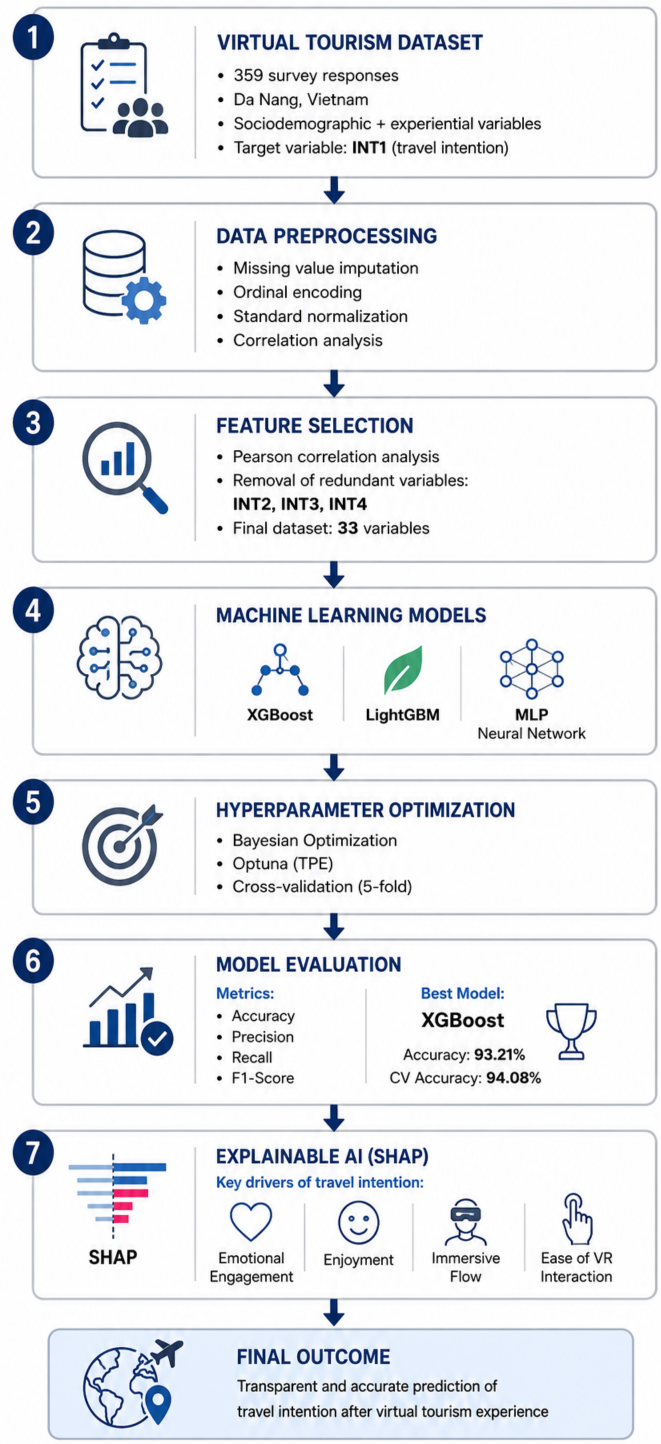

Fig. 1. Methodological Process

Da Nang, Vietnam [36]. Initially, the dataset included 36 variables: 6 sociodemographic and 30 related to psychological perceptions and virtual tourism experiences. We encoded the responses for the analysis as follows: Gender [1 = Male, 2 = Female], Marital status [1 = Single, 2 = Married, 3 = Other], Income group [1 to 4], Age group [1 to 3], Tourist group [1 The 30 measurement items were coded according to the scale indicated previously [1 to 5] e.g., ENJ4: "Using VR makes me feel happy".

TABLE II
CONSTRUCTS AND MEASUREMENT ITEMS USED IN THE VIRTUAL TOURISM SURVEY [36]

Constructs	Item Code	Description	**Scale**
Sociodemographic	Gender	Gender	1=Male 2=Female
	Marital Status	Marital Status	1=Single 2=Married 3=Other
	Income	Income group	1 to 4
	Age	Age group	1 to 3
	Tourist	Tourist group (Related to the number of trips this year	1 to 4
	VR	Have you ever heard of virtual reality?	1=Yes, 2=No
Presence	PRE1	I feel like I'm in the middle of the city when using VR on the Danang tourism destination website	1 to 5
	PRE2	I feel like my actual location is in Danang when experiencing VR on the Danang tourism destination website	
	PRE3	It seems like I am truly present in the virtual environment rendered by VR	
	PRE4	I feel that I can move around to explore the scenery and participate in tourist activities at the destination when using VR on the Danang tourism destination website	
Aesthetics	AES1	The website platform interface is designed sharply	
	AES2	The website platform interface design is beautiful	
	AES3	The layout of the website platform interface is attractive	
	AES4	The design of the website platform interface is artistic	
Usefulness	USE1	Using VR on the Danang tourism destination website brings benefits to me	
	USE2	Using VR on the Danang tourism destination website helps me gain more knowledge about this tourism destination	
	USE3	Using VR on the Danang tourism destination website helps me make friends/connect with others who have watched videos	
	USE4	VR on the Danang tourism destination website is very useful in improving the efficiency of receiving destination information	
Ease of Use	EAS1	It is very easy to use VR on the Danang tourism destination website	
	EAS2	I can easily use VR to explore what I want to know about the Danang tourism destination	
	EAS3	I can use VR on the Danang tourism destination website easily from anywhere	
Enjoyment	ENJ1	Using VR on the Danang tourism destination website makes me feel interested	
	ENJ2	Using VR on the Danang tourism destination website makes me feel excited	
	ENJ3	Using VR on the Danang tourism destination website makes me feel fun	
	ENJ4	Using VR on the Danang tourism destination website makes me feel happy	
Emotional Involvement	EMO1	I am completely drawn to engage in using VR on the Danang tourism destination website	
	EMO2	I am very impressed with the activities that can be performed when using VR on the Danang tourism destination website	
	EMO3	I feel immersed in the virtual environment from the VR experience on the Danang tourism destination website	
Flow State	FLOW1	During the use of VR on the Danang tourism destination website, I feel completely captivated	
	FLOW2	During the use of VR on the Danang tourism destination website, I feel that time passes by very quickly	
	FLOW3	During the use of VR on the Danang tourism destination website, I temporarily forget all external concerns	
	FLOW4	During the use of VR on the Danang tourism destination website, I forget where I am	
Visit Intention	INT1	I intend to visit Danang after experiencing this destination through VR on the Danang tourism destination website	
	INT2	I plan to visit Danang after experiencing this destination through VR on the Danang tourism destination website	
	INT3	I feel ready to visit Danang after experiencing this destination through VR on the Danang tourism destination website	
	INT4	I am willing to spend money and time to visit Danang after experiencing this destination through VR on the Danang tourism destination website	

For our analysis, the target variable was INT1, which quantifies the probability that a tourist will visit the destination after the virtual experience. Accurate modeling of this intention enables us to assess the impact of virtual tourism on decision making, providing valuable information to stakeholders in the tourism industry. To assess the level of class balance in the target variable (INT1), we analyzed the distribution of response classes before model training. This distribution did not show a significant imbalance between classes, supporting the use of accuracy, completeness, and the F1 score as evaluation metrics for model development.

B. *Exploratory Analysis Selection of the Target Variable*

To optimize predictive modeling, we perform a rigorous feature selection process based on correlation analysis and variance assessment. The objective is to determine whether INT1 adequately encapsulates the intention to travel without introducing redundant information.

1) Correlation Analysis

We evaluated the linear relationship between INT1 and INT2, INT3, and INT4 using the Pearson correlation coefficient [37]–[39], defined as:

$$\rho(X,Y) = \frac{\mathrm{Cov}(X,Y)}{\sigma_X \sigma_Y}, \tag{1}$$

where $\mathrm{Cov}(X,Y)$ is the covariance:

$$\mathrm{Cov}(X,Y) = \frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y}), \tag{2}$$

and σ_X, σ_Y are standard deviations:

$$\sigma_X = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2}, \quad \sigma_Y = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{3}$$

2) Selection Criterion for INT1

If the absolute value of the Pearson correlation coefficient satisfies $|\rho(INT1, INT_j)| > 0.7$ for $j \in \{2,3,4\}$, we consider INT_j redundant and remove it without significant loss of information. This criterion allows the identification of both strong positive and strong negative linear relationships, ensuring a more robust evaluation of variable redundancy. With correlations of 0.805 (INT2), 0.735 (INT3) and 0.708 (INT4), we conclude that INT1 encapsulates most of their information, reducing the need for additional predictors. Thus, we quantify the proportion of variance explained by a predictor X using:

$$R^2 = \rho^2(X, INT1), \tag{4}$$

where R^2 measures the variance in $INT1$ explained by X. Since we find that INT1 accounts for at least 50% of the variance in the other INTs, we determine that including them would introduce redundancy.

So, we select INT1 as the only predictor to reduce multicollinearity and improve the stability of the model. In doing so, we maintain predictive accuracy while optimizing computational efficiency, ensuring a robust and streamlined model. In this way, when deestimating INT2, INT3, and INT4, the data set used for the analysis was made up of 33 variables.

3) Data Normalization

To ensure the proper convergence of machine learning models, we apply feature normalization using standard scaling [40], [41]. This transformation is essential to prevent features with different magnitudes from disproportionately influencing the model. We use standard scaling to transform each feature so that the resulting distribution has zero mean and unit variance.

By normalizing features, we remove scale disparities between variables, ensuring that all features contribute equally to the learning process [42]. This transformation is for models that rely on gradient-based optimization, as it speeds up convergence and stabilizes weight updates. We performed preprocessing by applying mean imputation to missing values, ordinal encoding for Likert-type responses, and standardization to ensure model convergence. Furthermore, we evaluated multiple classifiers, including Random Forest, Logistic Regression, and XGBoost, under a 5-fold cross-validation scheme to ensure robustness.

C. Machine Learning Streategy: Predict Travel Intention

In this study, we implement three classification models: XGBoost, LightGBM, and MLP. Each model has distinct characteristics that are suitable for predicting travel intent after a virtual tourism experience. We perform a comparative analysis based on predictive accuracy, efficiency, and interpretability to determine the optimal model. The following sections provide a justification for their selection and evaluation criteria.

1) XGBoost Model

We employ XGBoost as a decision tree-based optimization algorithm due to its high performance capacity and its robustness against overfitting through regularization and gradient-based optimization [43]–[45]. The model optimizes a regularized loss function, expressed as:

$$L(\theta) = \sum_{i=1}^{n} L(y_i, f(X'_i)) + \sum_{k=1}^{K}\Omega(f_k), \tag{5}$$

where $L(y_i, f(X'_i))$ quantifies the deviation between the predicted value $f(X'_i)$ and the actual value y_i. The term $\Omega(f_k)$ corresponds to the regularization applied to each of the K trees, ensuring the generalization of the model and minimizing the overfitting.

We implemented XGBoost using an additive learning approach, where each new tree is trained to correct the residual errors of previous iterations. The iterative update of the prediction function is defined as follows.

$$F_{t+1}(X') = F_t(X') + \gamma h_t(X'), \tag{6}$$

where $F_t(X')$ represents the prediction of the model in iteration t, while $h_t(X')$ denotes the new tree, which is fitted to minimize the residual errors of $F_t(X')$. The parameter γ controls the contribution of the newly added tree, acting as a regularization factor to maintain the stability of the model.

To avoid overfitting, we integrate L1 and L2 regularization techniques (Lazo and Ridge), which impose constraints on the complexity of the learned function [46], [47].

L1 Regularization (Lasso):

$$\Omega(f_k) = \alpha \sum_{j=1}^{T}|w_j|, \tag{7}$$

where w_j represents the weights associated with the nodes of tree k, and α determines the magnitude of penalization, promoting sparsity in the learned parameters.

L2 Regularization (Ridge):

$$\Omega(f_k) = \lambda \sum_{j=1}^{T} w_j^2, \tag{8}$$

where λ acts as a penalty term that discourages excessively large weight values, enhancing model generalization.

2) LightGBM Model

We employ LightGBM as an advanced boosting-based model optimized for computational efficiency through its leaf-wise growth strategy [48]–[50]. This approach improves training speed, reduces memory consumption, and improves predictive performance in high-dimensional data sets.

Although LightGBM shares the objective of minimizing a regularized loss function with XGBoost, we differentiate it by its histogram-based optimization and leaf-wise growth strategy. The loss function is expressed as:

$$\mathcal{L}(\psi) = \sum_{p=1}^{N} \ell(y_p, g(X'_p)) + \beta \sum_{q=1}^{M} \|v_q\|^2, \tag{9}$$

where ψ represents the parameter space of the LightGBM model, $\ell(y_p, g(X'_p))$ measures the error between the prediction $g(X'_p)$ and the actual value y_p, β controls the regularization of L2 applied to the tree leaf weights v_q, X'_p denotes the normalized feature set, ensuring numerical stability.

We select the optimal leaf node H^* by maximizing the information gain, ensuring that each split effectively contributes to reducing the loss.

$$H^* = \arg\max_{H} \sum_{i\in H} G_i - \frac{1}{2}\frac{\left(\sum_{i\in H} G_i\right)^2}{\sum_{i\in H} H_i + \lambda}, \tag{10}$$

where G_i is the loss function gradient with respect to model prediction, H_i represents the second-order derivative (Hessian), ensuring numerical stability, and λ is the regularization parameter that controls model complexity.

3) MLP Model

We employ MLP as a non-linear model that captures complex relationships between input variables [50], [51]. Using multiple interconnected layers, each neuron processes inputs through a weighted sum, followed by an activation function:

$$z_j = \sum_{i=1}^{m} w_{ji} X'_i + b_j \tag{11}$$

$$a_j = f(z_j), \tag{12}$$

where X'_i represents the normalized inputs to ensure numerical stability, w_{ji} are the synaptic weights, determining input importance, b_j is the bias term, allowing the neuron to shift activation thresholds, $f(z_j)$ is the activation function, introducing non-linearity into the model. Now, and to enhance deep learning capabilities, we utilize the Rectified Linear Unit (ReLU) activation function:

$$f(x) = \max(0, x) \tag{13}$$

Like the authors [52] and [53], we select ReLU because of its ability to accelerate convergence and mitigate vanishing gradients, common in traditional sigmoid and tanh functions.

During training, we apply error backpropagation to iteratively update weights using gradient descent.

$$w_{ji}(t+1) = w_{ji}(t) - \eta \frac{\partial J}{\partial w_{ji}}, \tag{14}$$

where η represents the learning rate, controlling the update step, J is the loss function, measuring prediction error, $\frac{\partial J}{\partial w_{ji}}$ denotes the gradient of error with respect to the weights.

4) Hyperparameter Optimization

We optimize hyperparameters, which regulate the complexity, regularization, and learning rate of the model, using Bayesian optimization through Optuna [54]. Since these parameters are not learned directly from the data, their selection is formulated as an optimization problem.

$$\Theta^* = \arg\max_{\Theta} f(\Theta), \tag{15}$$

where Θ is the hyperparameter set, $f(\Theta)$ represents model performance, and Θ^* is the optimal configuration.

Unlike random search methods, Optuna models $f(\Theta)$ probabilistically and iteratively refines its estimates:

$$\Theta^* = \arg\max_{\Theta} \mathbb{E}[f(\Theta)], \tag{16}$$

where $\mathbb{E}[f(\Theta)]$ denotes the expected model performance. Optuna employs a Tree-structured Parzen Estimator (TPE) to partition the hyperparameter space into two probabilistic distributions [55], [56]:

$$p(\Theta \mid f(\Theta)) = \begin{cases} g(\Theta), & \text{if } f(\Theta) \text{ is high} \\ l(\Theta), & \text{otherwise} \end{cases}, \tag{17}$$

where $g(\Theta)$ models promising hyperparameters, while $l(\Theta)$ represents suboptimal configurations. By prioritizing values likely to improve performance, we accelerate convergence while maintaining computational efficiency.

In the hyperparameter configuration process, we evaluated multiple options for each parameter using Optuna-based Bayesian optimization. For the XGBoost model, the search space included: number of estimators from 20 to 200, maximum tree depth from 3 to 12, learning rate from 0.01 to 0.30, subsample ratio from 0.6 to 1.0, column sampling ratio (`colsample_bytree`) from 0.6 to 1.0, and regularization parameters α and λ from 0 to 10. For LightGBM, we additionally evaluated the number of leaves (between 15 and 100) and the minimum number of child samples (between 5 and 30). For the MLP model, we tested hidden layer sizes of 32, 64, and 128 neurons, learning rates between 0.0001 and 0.01, and batch sizes of 16, 32, and 64.

We performed the optimization process on 50 Optuna trials using five-fold cross-validation. Table III, we present the final hyperparameter configuration corresponding to the best-performing trial obtained during the Bayesian optimization procedure.

TABLE III
FINAL OPTIMIZED HYPERPARAMETERS FOR THE EVALUATED MODELS

Model	Hyperparameter	Selected Value
XGBoost	n_estimators	63
	max_depth	8
	learning_rate	0.1180
LightGBM	num_leaves	31
	min_child_samples	20
	learning_rate	0.1000
MLP	hidden_layer_sizes	64
	learning_rate_init	0.001
	batch_size	32

5) Model Evaluation

We evaluated the predictive performance of our selected models using standard classification metrics, including accuracy, precision, recall, and the F1 score. These metrics are widely used to assess classification tasks and are defined based on the relationships between true positives, false positives, and false negatives

To ensure robustness, we applied the K cross-validation and report the average precision across folds. This provides a more stable estimate of model generalization performance and mitigates overfitting. This evaluation framework ensures a rigorous and interpretable comparison of model effectiveness across classifiers.

6) Interpretable Feature Analysis with SHAP

Gaining insight into the influence of features on our non-linear model is crucial for ensuring interpretability [61]. To achieve this, we used SHAP analysis to quantify the impact of each feature on the predictions.

We define the SHAP values mathematically as follows: Given an instance x, the SHAP value for the feature j is:

$$\phi_j = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} \left[v(S \cup \{j\}) - v(S) \right], \tag{18}$$

where N is the full set of features, S is any subset excluding j, and $v(S)$ represents the model's prediction using only S. The formula ensures an equitable distribution of importance across all possible feature subsets.

We ensure that SHAP values conform to the following fundamental mathematical principles [62]:

- **Efficiency:** The total contribution of all features sums to the difference between the model prediction with all features and the baseline prediction:

$$\sum_{j=1}^{|N|} \phi_j = v(N) - v(\emptyset) \tag{19}$$

- **Symmetry:** If two features contribute equally across all subsets, they receive identical SHAP values:

$$v(S \cup \{j\}) = v(S \cup \{k\}) \quad \forall S \Rightarrow \phi_j = \phi_k \tag{20}$$

- **Additivity:** For two models v_1 and v_2, their combined contributions satisfy:

$$\phi_j(v) = \phi_j(v_1) + \phi_j(v_2) \tag{21}$$

We applied SHAP to analyze the importance of features in our optimized model to predict INT1. This ensures that beyond achieving high predictive accuracy, our model provides insight into the most influential variables, facilitating data-driven decision-making in virtual tourism [31], [63].

IV. RESULTS

We evaluated the predictive models based on their ability to estimate INT1, which quantifies the likelihood that a user visits Da Nang after experiencing virtual tourism. To ensure a rigorous assessment, we conducted a comparative evaluation of XGBoost, LightGBM, and MLP, analyzing their performance in terms of accuracy, precision, recall, and F1 score.

Additionally, we applied cross-validation to validate model robustness and employed Bayesian optimization to fine-tune hyperparameters, enhancing predictive performance. To further improve the interpretability of the model, we incorporated SHAP to quantify the contribution of each feature to INT1 predictions, ensuring that our approach not only achieves high predictive accuracy, but also provides transparency in identifying the key factors that influence user travel intent.

1) Model Performance Analysis

We evaluated the predictive performance of XGBoost, LightGBM, and MLP using accuracy, precision, recall, F1 score, and mean CV accuracy (MCVA). The results, summarized in Table IV, indicate that gradient boost models outperform the neural network-based approach.

TABLE IV
PERFORMANCE COMPARISON OF MACHINE LEARNING MODELS

Model	Accuracy	Precision	Recall	F1-Score	MCVA
XGBoost	0.9028	0.9046	0.9028	0.9023	0.9234
LightGBM	0.8889	0.8915	0.8889	0.8888	0.9129
MLP	0.8333	0.8401	0.8333	0.8235	0.8399

We observe that XGBoost achieves the highest accuracy (0.9028) and the best generalization across cross-validation folds (0.9234). LightGBM follows closely, with an accuracy of 0.8889, while MLP performs the weakest, particularly in recall and the F1 score. The results confirm that tree-based boost models are more effective for this classification task.

To provide a more comprehensive evaluation of the optimized XGBoost model, we present in Table V complementary classification metrics, including ROC-AUC, precision, recall, F1-score, and cross-validation accuracy.

TABLE V
EVALUATION METRICS FOR THE OPTIMIZED XGBOOST MODEL

Metric	Value
Accuracy	0.9321
Precision	0.9046
Recall	0.9028
F1-score	0.9023
Cross-validation accuracy	0.9408
ROC-AUC	0.9010

2) XGBoost Performance with Cross-Validation

We apply a five-fold cross-validation to assess the stability and generalization of XGBoost. This procedure ensures that model performance is evaluated across multiple train-test partitions, mitigating biases introduced by a single split. We calculate the mean accuracy and depict the accuracy distribution across the folds in Fig. 2.

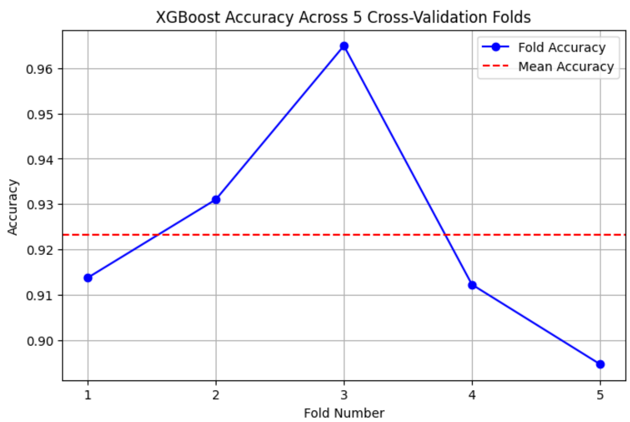

Fig. 2. Accuracy of XGBoost Model Across Five Cross-Validation Folds.

We achieve a mean cross-validation accuracy of 0.9234, confirming that XGBoost maintains strong generalization. However, we observe moderate variation across folds, with an accuracy ranging from approximately 0.90 to 0.97. This indicates some sensitivity to data partitioning, but the model remains robust overall. The slight fluctuations highlight the importance of cross-validation in mitigating overfitting risks and ensuring reliable evaluation metrics.

3) Optimized XGBoost Model with Hyperparameter Tuning

To further enhance XGBoost's predictive performance, we apply Bayesian optimization using Optuna. We explore multiple hyperparameter configurations, iteratively refining our selection based on performance feedback. The optimal hyperparameters identified are:

- **Number of Estimators**: 63
- **Maximum Depth**: 8
- **Learning Rate**: 0.1180

Fig. 3 illustrates the evolution of the best objective value in successive trials. We observe that as trials progress, Optuna incrementally improves hyperparameter selection, identifying configurations that maximize model accuracy.

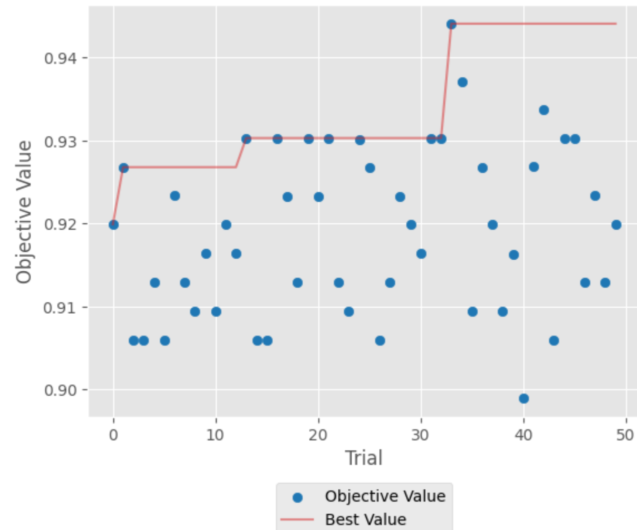

Fig. 3. Progression of XGBoost Model Accuracy During Optuna-Based Hyperparameter Tuning.

With these optimized hyperparameters, we achieve an accuracy of 0.9321 and a cross-validation accuracy of 0.9408. Our results confirm that Bayesian optimization effectively balances model complexity and predictive power, leading to improved generalization and robustness.

Among the models tested, XGBoost achieved the highest precision and CV accuracy, confirming its superiority in predicting INT1. The optimized hyperparameters further enhanced its performance, demonstrating that a carefully tuned gradient boosting model provides the most reliable estimation of user travel intent. These results validate INT1 as a robust indicator of user decision making in virtual tourism and highlight XGBoost as the most effective tool for predictive analysis.

4) Interpretable Analysis with SHAP: Understanding the Determinants of Travel Intent to Da Nang

We employed XGBoost due to its robustness on tabular data and support for SHAP-based interpretation. SHAP values allow individual-level explanation of predictions, which is crucial for transparent decision-making in applications such as accessibility, tourism, and public services.

To complement the quantitative evaluation of our models, we performed a SHAP analysis to interpret how individual characteristics contribute to predicting the intention to visit Da Nang ($INT1$). We identify the most influential factors driving the intention to travel. The horizontal axis represents SHAP values, indicating the magnitude and direction of each feature's effect on model predictions. Features with larger absolute SHAP values exhibit greater predictive influence. The color gradient represents the feature values, where red corresponds to higher values and black corresponds to lower values.

The analysis reveals that emotional engagement, enjoyment, and perceptions of the flow state are the strongest determinants of the intention to travel.

Our findings align with established theories in tourism and consumer behavior, reinforcing that strong emotional engagement, immersive presence, and seamless usability significantly enhance travel intent. The hierarchical ranking of feature importance confirms the model's capability to capture user experience dynamics in a virtual tourism setting.

5) Individualized SHAP Analysis: Tourist-Level Interpretation

To further refine our interpretability analysis, we evaluate SHAP values at the individual level, evaluating how specific characteristics influence the predicted travel intent ($INT1$) for two representative tourists. Figs. 4 and 5 illustrate the personalized contributions of key variables for Tourist 25 and Tourist 61, respectively.

Tourist 25: Low Intention to Visit Da Nang

In contrast, Tourist 25 has a significantly lower predicted travel intent, with $f(x) = 0.22$, well below the base value. Despite high immersion and usability ratings, the negative influence of financial constraints and excessive detachment from reality result in a low travel intent prediction. This highlights the importance of balancing virtual immersion with practical feasibility when designing tourism experiences.

Tourist 61: High Intention to Visit Da Nang

For Tourist 61, the final prediction of the intention of traveling is $f(x) = 3.12$, significantly above the base value of 1.168, indicating a strong intention to visit Da Nang, driven by high immersion, emotional engagement, and ease of VR interaction. This confirms that positive psychological and experiential responses to virtual tourism substantially improve travel decision making.

These individual-level analyzes reinforce our broader findings that emotional engagement and ease of use play a central role in predicting travel intent. However, personal financial limitations and extreme immersion effects introduce variability in travel decision making. These insights provide valuable guidance for tailoring virtual tourism experiences to diverse user profiles.

Beyond the analysis of individual tourists, the SHAP-based interpretability framework enables the identification of broader behavioral patterns associated with travel intention. In general, tourists exhibiting high predicted intention to visit Da Nang tend to demonstrate strong emotional engagement, positive enjoyment responses, immersive flow experiences, and ease of interaction with the virtual environment. Conversely, lower travel intention is frequently associated with practical concerns, weaker emotional connection, reduced perceived value, or excessive detachment from reality during the virtual experience.

V. Discussion

Our study presents a machine learning framework to predict travel intent ($INT1$) based on virtual tourism experiences. By integrating advanced models, Bayesian hyperparameter optimization, and interpretable machine learning (SHAP), we achieve high predictive accuracy and model explainability. Our method captures complex, non-linear relationships between psychological, experiential, and demographic variables, offering a comprehensive understanding of the factors that influence the intent of travel.

A key advantage of our methodology is its interpretability, which bridges the gap between predictive performance and actionable insights. The SHAP analysis highlights the dominant role of emotional involvement ($EMO1$), enjoyment ($ENJ4, ENJ3$), and immersive flow ($FLOW3, FLOW2$) in shaping travel intent. Higher values in these characteristics are strongly associated with an increased likelihood of visiting Da Nang, strengthening theories that the effectiveness of virtual tourism depends on user engagement, presence, and positive emotional response. Furthermore, individual-level SHAP interpretations reveal that personal characteristics, such as tourist type and prior exposure to VR, modulate travel intent differently between users. We selected Tourist 25 and Tourist 61 for the individualized SHAP analysis because they represent contrasting profiles within our data set. Tourist 25 exhibited one of the lowest predicted levels of travel intention, while Tourist 61 showed one of the highest. This contrast allowed us to illustrate how our model interprets and weighs psychological and demographic characteristics differently for users with low versus high predicted intent.

Despite its strengths, our study has limitations. This data is exclusively associated with virtual tourism experiences related to Da Nang, Vietnam; however, it was sufficient for the SHAP-based machine learning and explainability comparative analyses conducted in this research. Therefore, the results should be interpreted within the context of the analyzed sample and the virtual tourism environment, which reflects specific territorial, cultural, socioeconomic, and tourism dynamics. Consequently, user behavior patterns and determinants of travel intention identified in this context may differ in destinations with distinct tourism ecosystems, levels of digital adoption, or traveler profiles. Furthermore, SHAP provides a rigorous interpretability framework, but does not establish causal relationships and our model does not account for external factors in real-time, such as travel restrictions, economic fluctuations, or dynamic marketing campaigns, which could significantly influence travel intent. While we identify key predictors, more research should incorporate causal inference techniques to validate the directionality of these effects. Although the proposed methodology is designed to be scalable and adaptable, additional validation using datasets from other cities, countries, and tourism environments is necessary to evaluate the robustness and transferability of the framework across heterogeneous territorial contexts. Future research should therefore incorporate multicity and cross-cultural datasets to assess whether the predictive relationships identified in this study remain stable under different tourism dynamics and destination characteristics.

In general, this study demonstrates that machine learning, combined with explainability techniques, provides a powerful framework to understand travel behavior in virtual environ-

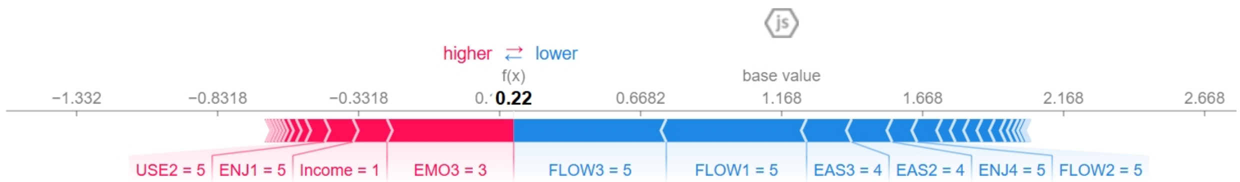

Fig. 4. SHAP Force Plot for Tourist 25: Low Predicted Travel Intention Due to Emotional Disengagement and Practical Barriers.

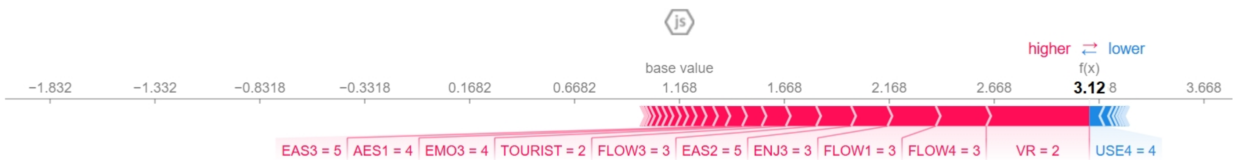

Fig. 5. SHAP Force Plot for Tourist 61: High Predicted Travel Intention Driven by Immersion and Emotional Engagement.

ments. Similarly, the findings of the present study revealed that psychological engagement-related variables, particularly emotional engagement, enjoyment, immersion, and flow state, were among the most influential predictors of travel intention within virtual tourism environments. However, unlike previous studies that primarily relied on traditional statistical analyses or theory-driven behavioral models [12], [33]–[35], the proposed framework integrates multiple machine learning models with SHAP-based explainability techniques, enabling both high predictive performance and transparent interpretation of tourist behavior. Therefore, the proposed approach not only confirms findings previously reported in the literature but also extends current knowledge by incorporating interpretable artificial intelligence techniques into virtual tourism analytics and travel intention prediction.

Although the dataset employed is relatively small, we deliberately focused on ensemble-based models such as XGBoost and LightGBM due to their superior ability to handle nonlinear interactions, feature importance analysis, and robustness on tabular data. Although simpler models may offer computational efficiency and easier implementation, they often fail to capture complex relationships among psychological and experiential factors. We selected more advanced models to exploit these interactions and paired them with SHAP values to enhance interpretability. This approach not only provides strong predictive accuracy, but also provides individualized and transparent explanations, offering meaningful support for decision-making in virtual tourism contexts.

VI. Conclusions

In this study, we proposed an advanced machine learning framework to predict the intention to travel ($INT1$) to Da Nang, Vietnam, based on virtual tourism experiences. Our methodology integrates three state-of-the-art models (XGBoost, LightGBM, and MLP), cross-validation, Bayesian hyperparameter optimization with Optuna, and SHAP-based interpretability. This approach enables not only high predictive accuracy but also transparency in model decisions, addressing the limitations of black-box models in travel behavior analysis. Using SHAP values, we provide a mathematical foundation for quantifying feature contributions, ensuring that our model is interpretable.

Our results demonstrate the superiority of XGBoost, achieving an accuracy of 93.21% and a cross-validation accuracy of 94.08%, surpassing traditional models. The SHAP analysis reveals that key psychological factors, such as emotional engagement ($EMO1$), enjoyment ($ENJ4, ENJ3$), and immersive flow ($FLOW3, FLOW2$) significantly influence travel intent. At an individual level, SHAP provides personalized insight into how each feature affects different users, confirming that the intention to travel is shaped by psychological engagement and demographic characteristics. The interpretability of our model ensures that decision makers can trust and use these insights effectively.

To further enhance our methodology, future work should integrate dynamic data sources in real-time, such as sentiment analysis of social networks, economic indicators, and personalized recommendation systems.

Limitations include potential cultural biases in travel intention modeling and the small dataset size, which could limit scalability. We acknowledge that rural or underserved populations may experience limited Internet access, which could affect the applicability of our framework. To mitigate this, we suggest that future research incorporates adaptive interfaces for low-bandwidth environments. Also, we consider it essential to state that our model complies with the requirements of the GDPR since it operates exclusively with anonymized data without personal identifiers.

The feasibility of implementing this strategy in real-world tourism applications is promising. The proposed framework requires a combination of computational resources for model training and expertise in machine learning deployment. Tourism stakeholders, including destination marketers and virtual tourism platforms, can adopt this approach to optimize user engagement, enhance marketing strategies, and improve virtual tourism experiences. We believe that the proposed model could be deployed on virtual tourism platforms at relatively low cost, as it is based on open-source frameworks. In future applications, usability testing should be conducted to adapt the system for individuals with disabilities or reduced digital skills. Ensuring the availability of high-quality user interaction data and a scalable infrastructure will be critical for a successful deployment. Our study embraces user-centered design principles, echoing global calls for inclusive technology ecosystems.

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