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RESEARCH ARTICLE

# Study on Tourism Development Using CRITIC Method for Tourist Satisfaction

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**ABSTRACT** This paper presents a novel approach for evaluating tourist satisfaction and developing optimized strategies by integrating the CRITIC method, deep learning with Multilayer Perceptron (MLP), and Genetic Algorithms (GA). The CRITIC method was employed to calculate the weights of various satisfaction indicators, such as accommodation quality and local services, based on their variance and correlation. These weights informed the MLP model, which accurately predicted tourist satisfaction with a mean absolute error (MAE) of 0.12 and a root mean square error (RMSE) of 0.18. Using the GA, the study identified optimal strategy combinations that improved satisfaction scores by up to 15% compared to baseline strategies. The integration of CRITIC, MLP, and GA provided a comprehensive framework that not only enhanced the accuracy of satisfaction evaluations but also optimized development strategies effectively. This approach demonstrated significant improvements in tourist satisfaction across various regions, with notable results including an increase in satisfaction scores from 4.0 to 4.3 in specific areas. The paper highlights the efficacy of combining these advanced methods to address complex evaluation and optimization challenges in tourism. Key contributions include the development of a robust, data-driven methodology for strategy optimization and the provision of actionable insights into satisfaction drivers, offering a valuable tool for tourism managers and policymakers. Future research directions involve expanding the methodology to different tourism sectors and incorporating real-time data for even more dynamic evaluations.

**INDEX TERMS** Tourist satisfaction, CRITIC method, deep learning (MLP), genetic algorithm (GA), satisfaction evaluation, strategy optimization, predictive modeling.

## I. INTRODUCTION

Tourism has become one of the most significant industries in the global economy, driving economic growth, fostering cultural exchange, and contributing to sustainable development. The increasing competitiveness in the tourism sector has compelled destinations to focus on maintaining and enhancing tourist satisfaction to ensure long-term success [1]. Tourist satisfaction is a critical determinant of repeat visits, positive reviews, and overall destination loyalty, which are essential for sustainable tourism development. As tourism continues to grow, so does the demand for strategic planning that incorporates comprehensive satisfaction evaluations. Effective strategic planning ensures that tourist needs and preferences are met, enhancing the destination's appeal and fostering sustainable tourism practices [2]. The role of tourism in sustainable development cannot be overstated. Tourism directly contributes to multiple Sustainable Development Goals (SDGs), including economic growth, job creation, environmental conservation, and cultural preservation [3]. To ensure sustainable tourism, destinations must balance the needs of tourists, local communities, and the environment. Evaluating tourist satisfaction is crucial in this context as it provides insights into areas that need improvement, ensuring that tourism growth aligns with sustainable practices. The process of evaluating satisfaction, however, is complex, as it involves various factors such as accommodation quality, service delivery, infrastructure,

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and the overall experience. Traditional methods of evaluating tourist satisfaction, including surveys, interviews, and observational studies, have been widely used but often lack the precision and adaptability required in today's dynamic tourism environment [4]. These methods typically rely on qualitative assessments or basic statistical analyses that fail to capture the complexity of tourist experiences and their evolving expectations. In an era marked by rapid technological advancements and data availability, the need for a more sophisticated approach to satisfaction evaluation and strategic planning has emerged. Conventional methods for tourist satisfaction evaluation have several limitations. Surveys and interviews, for example, depend on subjective responses and are prone to biases related to the design of the questionnaire, the sample population, and the timing of data collection. These methods are static, meaning they are based on a snapshot of opinions at a specific moment in time, making it difficult to adapt to changing preferences or trends. Such evaluations often fail to leverage the vast amount of available data, such as online reviews, social media interactions, and real-time behavioral data from tourists. The tourism industry is increasingly recognizing the importance of data-driven decision-making and predictive analysis to address the challenges of dynamic and complex tourist preferences. Traditional evaluation methods do not efficiently handle large datasets or multidimensional factors, making it difficult to predict future trends or to adapt to emerging changes in tourist behavior. This has led to the exploration of advanced techniques that integrate artificial intelligence (AI) and optimization algorithms to provide more accurate, real-time, and actionable insights. The integration of AI techniques, particularly deep learning models, with optimization algorithms offers a promising solution. Deep learning models can process and analyze large datasets, identifying patterns and trends that would otherwise go unnoticed [5]. By combining deep learning with optimization algorithms such as Genetic Algorithms (GA), it is possible to enhance the process of evaluating tourist satisfaction and developing effective strategies that cater to the specific needs of tourists. The CRITIC (Criteria Importance Through Intercriteria Correlation) method, a robust multi-criteria decision-making tool, can be used to assign appropriate weights to the various factors influencing tourist satisfaction, improving the accuracy of evaluations.

Tourist satisfaction evaluation has been extensively studied in the literature, with numerous approaches focusing on identifying and measuring the factors that influence the overall tourist experience. Traditional methods such as Likert scale surveys and interviews have been the predominant tools for gathering tourist feedback. These methods, however, are limited by their reliance on subjective opinions and their inability to process large datasets or capture real-time data. The rise of big data and AI has prompted researchers to explore more advanced methods for evaluating satisfaction, offering the potential for more nuanced and dynamic analyses. In recent research, deep learning and reinforcement learning (RL) approaches have been widely applied to various domains, including tourism, security, and network reconfiguration. These technologies showcase significant advancements in predictive and adaptive systems, allowing researchers and practitioners to harness large amounts of data for enhanced decision-making. Iqbal et al. [6], for example, examined tourist behavior using DeepSentiBank for sentiment prediction and Kernel Density Estimation (KDE) to analyze spatiotemporal tourist activity patterns. This research provided valuable insights for tourism management by identifying key areas of interest and improving the overall tourist experience [6]. Wang and Hu [7] developed a deep reinforcement learning-based route planning system for travel recommendations, enhancing navigation adaptability through value iteration networks. Their work demonstrated how deep learning could improve tourist satisfaction by offering more personalized and efficient travel experiences [7]. Similarly, Hilali et al. compared Faster R-CNN and YOLOv7 for object detection in tourist photos, concluding that YOLOv7's superior precision and recall made it more effective for detecting places of interest in photos, which is important for tourism services that depend on visual recognition [8]. In the realm of Halal food identification, Tarannum et al. [9] utilized YOLOv5 and machine learning for accurate classification of Halal food items, addressing a specific need for Muslim tourists. Their work demonstrated how deep learning models could be adapted for specialized tourism needs [9]. Bhatti et al. [10] applied YOLOv4 for real-time weapon detection in CCTV footage, providing a solution for enhancing security in tourist destinations. These applications of deep learning across different domains reflect the potential of AI technologies to revolutionize tourism management, particularly in areas like satisfaction evaluation, service enhancement, and safety improvements [10]. Gholizadeh et al. explored various RL algorithms, including deep Q-learning and soft actor-critic, for distribution network reconfiguration, optimizing electrical grid performance by reducing action space and improving loss reduction [11]. Lei et al. discuss the integration of DRL with the Internet of Things (IoT), introducing autonomous IoT (AIoT) and presenting a comprehensive survey and model for AIoT decision-making while highlighting future challenges [12]. Yang et al. propose a Double Bootstrapped Soft-Actor–Critic-Discrete (DBSAC-D) algorithm to enhance decision-making for autonomous vehicles, achieving faster convergence and better performance in traffic scenarios [13]. In another work, Yang et al. introduce a Modified Proximal Policy Optimization (PPO) algorithm for urban traffic control within Software Defined IoT (SD-IoT), improving system-wide traffic efficiency by controlling both vehicles and traffic lights [14]. Lastly, Agnesina et al. apply DRL to optimize VLSI placement parameters, achieving significant wire length reductions and faster iteration times compared to both human engineers and existing auto-tuners, demonstrating the versatility of DRL across diverse technical challenges [15]. These studies reflect the growing trend of leveraging deep learning and RL algorithms to enhance user experiences, optimize system efficiency, and address complex challenges across diverse sectors such as tourism, food security, surveillance, and energy management.

The CRITIC method is a popular approach in multi-criteria decision-making (MCDM) because it provides a systematic way of assigning weights to different criteria based on the correlation and contrast between them. In tourism research, the CRITIC method has been used to evaluate factors such as service quality, tourist expectations, and destination appeal. By considering both the variation in data and the interdependence of criteria, CRITIC allows for a more objective weighting process, improving the reliability of satisfaction evaluations. Deep learning models, particularly Multilayer Perceptrons (MLP), have been applied in tourism data analysis to predict tourist satisfaction [16]. MLPs are well-suited for handling complex datasets with multiple inputs, allowing for more accurate predictions of tourist behavior and satisfaction levels. These models can analyze data from various sources, including online reviews, social media posts, and surveys, providing a comprehensive view of tourist preferences and expectations. Genetic Algorithms (GA) have been widely used in optimization problems, including in the tourism industry. GAs are particularly effective in scenarios where there are multiple potential solutions and the goal is to find the most optimal one. In the context of tourist satisfaction, GAs can be used to optimize the development of tourism strategies, such as improving infrastructure, service quality, or marketing campaigns, based on the predicted satisfaction levels from the MLP model. By integrating GAs with deep learning models, tourism managers can develop strategies that are both data-driven and optimized for maximum impact. The primary objective of this paper is to integrate the CRITIC method, MLP, and GA to improve the evaluation of tourist satisfaction and the development of tourism strategies. The CRITIC method will be used to assign appropriate weights to the various satisfaction factors, while the MLP model will predict satisfaction levels based on these factors [17]. The GA will then optimize the development strategies to enhance overall tourist satisfaction. This paper's contribution lies in its novel combination of the CRITIC method, deep learning (MLP), and genetic algorithm (GA) for tourist satisfaction evaluation and strategy development. The proposed approach offers a more accurate, data-driven method for predicting satisfaction and optimizing tourism strategies, with the potential to significantly improve destination management and strategic planning in the tourism industry. The paper is organized as follows: the next section provides a detailed methodology for integrating the CRITIC method, MLP, and GA. Following that, the experimental setup and results are presented, including a case study application. The paper concludes with a discussion of the results and their implications for the tourism industry, along with suggestions for future research.

## II. PROBLEM FORMULATION

Tourist satisfaction is a multifaceted concept influenced by various indicators, which can be categorized into several key factors. Accommodation Quality includes aspects such as room cleanliness, comfort, amenities, and overall service provided by hotels or lodgings. High-quality accommodation is often a fundamental factor contributing to positive tourist experiences. Local Services encompasses the availability and quality of services provided at the destination, such as transportation, dining, shopping, and customer service. Efficient and high-quality local services can significantly enhance the overall satisfaction of tourists [18]. The richness of cultural experiences, including historical sites, local traditions, festivals, and activities, plays a crucial role in shaping tourists' perceptions and satisfaction. Engaging cultural experiences can differentiate a destination and attract visitors. Environmental Factors include the cleanliness, safety, and general environmental conditions of the destination. A well-maintained and safe environment is essential for ensuring a pleasant and enjoyable stay for tourists. Each of these factors can influence tourists' overall satisfaction, and their relative importance may vary depending on the destination and the preferences of the tourists. Evaluating these indicators comprehensively is essential for understanding and improving tourist satisfaction. Traditional statistical methods for evaluating tourist satisfaction, such as surveys and interviews, have several limitations. Conventional methods often struggle with large datasets, particularly when integrating diverse sources of data such as online reviews, social media posts, and real-time feedback. These methods may be unable to process and analyze vast amounts of information efficiently [19]. Traditional approaches may not adequately capture complex interactions between different satisfaction factors. For instance, the interplay between accommodation quality and local services or the combined effect of cultural experiences and environmental factors on overall satisfaction is often overlooked. Survey-based methods are subject to biases related to respondents' opinions, question phrasing, and sampling methods. These biases can affect the accuracy and reliability of the satisfaction evaluation. Conventional methods typically provide a snapshot of tourist satisfaction at a particular point in time, which may not reflect evolving preferences or trends. This limitation makes it challenging to adapt strategies based on changing tourist expectations. Traditional methods often focus on descriptive statistics rather than predictive modeling, limiting their ability to forecast future satisfaction levels or to adapt to emerging trends. To address these challenges, there is a need for more advanced, data-driven approaches that can handle large volumes of data, capture complex interactions, and provide predictive insights.

### A. MATHEMATICAL REPRESENTATION OF SATISFACTION

To formulate the problem of evaluating tourist satisfaction mathematically, we consider the following approach:

1. Defining Satisfaction Factors: Let $F_1, F_2, \ldots, F_n$ represent the key factors influencing tourist satisfaction, such as accommodation quality, local services, cultural experiences, and environmental factors. Each factor $F_i$ is associated with a satisfaction score $s_i$ derived from data sources such as surveys, reviews, and observations.

2. CRITIC Method for Weighting Factors: The CRITIC method assigns weights to these factors based on their importance and intercriteria correlation. The weight $w_i$ for each factor $F_i$ is determined by analyzing the variation and correlation among the factors. The weight $w_i$ reflects the relative importance of factor $F_i$ in the overall satisfaction evaluation.

$$w_i = \frac{C_i}{\sum_{j=1}^{n} C_j} \tag{1}$$

where $C_i$ is a measure of the contrast intensity of factor $F_i$, computed based on its variation and correlation with other factors.

3. Satisfaction Prediction Model: Using the weights $w_i$ derived from the CRITIC method, the overall tourist satisfaction score $S$ can be predicted as a weighted sum of the satisfaction scores of individual factors:

$$S = \sum_{i=1}^{n} w_i \cdot s_i \tag{2}$$

This equation represents a linear model where each factor's contribution to overall satisfaction is scaled by its respective weight.

The formulated equations significantly advance the paper's contribution to tourist satisfaction evaluation and strategy development by integrating sophisticated mathematical techniques with cutting-edge optimization algorithms. The advanced Layer 1 Objective Function, utilizing eigenvalue decomposition, ensures precise weighting of satisfaction factors, capturing complex interactions with high accuracy. The Layer 2 Objective Function incorporates a time-dependent cost function, accounting for dynamic fluctuations and operational costs over time, which leads to more adaptable and robust strategies. The comprehensive set of constraints, including budget, resource, quality, operational, and environmental considerations, ensures that the proposed solutions are feasible, sustainable, and aligned with practical requirements. By integrating Deep Learning (MLP) and Genetic Algorithms (GA) with the CRITIC method, the model leverages sophisticated pattern recognition and optimization capabilities, enhancing strategic decision-making and adaptability [20]. This novel approach, with its mathematical rigor and innovative framework, provides actionable insights and solutions that are both theoretically sound and practically implementable, offering significant improvements over conventional methods and setting a new standard for evaluating and optimizing tourist satisfaction.

### 1) OBJECTIVE FUNCTION

Objective Function (Layer 1): The goal is to maximize the overall tourist satisfaction $S$, which is a weighted sum of individual satisfaction factors. We can use advanced mathematical operations like matrix multiplication and eigenvalue-based weighting.

$$\text{Maximize } S = \mathbf{w}^T \mathbf{s} \tag{3}$$

where $\mathbf{w}$ is the Weight vector derived from the CRITIC method, $\mathbf{w} = [w_1, w_2, \ldots, w_n]^T$. $\mathbf{s}$ is the Satisfaction score vector, $\mathbf{s} = [s_1, s_2, \ldots, s_n]^T$.

To derive $\mathbf{w}$, we use the eigenvalue decomposition of the correlation matrix $\mathbf{C}$:

$$\mathbf{C} = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^T \tag{4}$$

where $\mathbf{V}$ is the Matrix of eigenvectors. $\mathbf{\Lambda}$ is the Diagonal matrix of eigenvalues.

Weights $\mathbf{w}$ are computed as:

$$\mathbf{w} = \frac{\mathbf{V}\mathbf{\Lambda}^2\mathbf{V}^T\mathbf{d}}{\sum_{i=1}^{n} \mathbf{V}\mathbf{\Lambda}^2\mathbf{V}^T\mathbf{d}_i} \tag{5}$$

where $\mathbf{d}$ is a vector representing the dispersion of satisfaction scores.

Objective Function Layer 2: Strategy Optimization:

$$\text{Maximize } Z = \alpha\left(\mathbf{w}^T\mathbf{s}\right) - \beta\left(\int_0^T C(\mathbf{x}(t))\,dt\right) \tag{6}$$

where $\alpha$ and $\beta$ is the Weight factors. $C(\mathbf{x}(t))$ is the Time-dependent cost function of strategy $\mathbf{x}(t)$, modeled as:

$$C(\mathbf{x}(t)) = \int_0^t \left(\mathbf{x}^T\mathbf{Q}(t)\mathbf{x} + \mathbf{x}^T\mathbf{R}(t)\mathbf{x} \cdot \sin(\omega t)\right) dt \tag{7}$$

where $\mathbf{Q}(t)$ and $\mathbf{R}(t)$ are time-varying cost matrices, and $\omega$ is a frequency parameter.

### 2) CONSTRAINTS

$$\int_\Omega \left(\mathbf{c}^T\mathbf{x}(t) + \alpha\|\nabla\mathbf{x}(t)\|^2\right) dt \leq B \tag{8}$$

where $\alpha$ is a regularization parameter controlling smoothness, $\|\nabla\mathbf{x}(t)\|$ is the gradient norm of the decision variable vector $\mathbf{x}$.

2. Resource Availability Constraint:

$$\sum_{k=1}^{K} \left(\mathbf{r}_k^T\mathbf{x} \cdot e^{-\lambda_k t_k}\right) \leq R \tag{9}$$

where $\lambda_k$ is a decay factor accounting for resource depletion over time, $t_k$ is a time parameter for resource usage.

3. Quality Constraint:

$$\frac{\partial s_i}{\partial t} \geq \log\left(Q_{\min,i} + \epsilon_i \cdot e^{\beta t}\right) \tag{10}$$

where $\beta$ is a growth rate parameter.

4. Maximum Satisfaction Score Constraint:

$$s_i \leq S_{\max,i} \cdot \left(1 + \frac{\eta_i}{\sqrt{1 + \sum_{j=1}^{n} \sigma(s_i, s_j) \cdot \cosh(\kappa_{ij})}}\right) \tag{11}$$

where $\sigma(s_i, s_j)$ is the covariance between satisfaction scores, $\cosh(\kappa_{ij})$ is the hyperbolic cosine function capturing the interaction between factors.

5. Operational Limit Constraint:

$$\mathbf{o}^T \mathbf{x} \leq \left(\int_0^T \mathbf{o}(t)dt\right) \cdot \exp\left(-\gamma \|\mathbf{x}\|_2\right) \tag{12}$$

where $\gamma$ is an exponential decay factor dependent on the norm of $\mathbf{x}$.

6. Time Constraint:

$$\int_0^T \mathbf{t}(t)^T \mathbf{x}(t) \cdot e^{-\rho t} dt \leq T_{\max} \tag{13}$$

where $\rho$ is a discount factor over time.

7. Environmental Impact Constraint:

$$\mathbf{e}^T \mathbf{x} \leq \frac{E}{1 + \alpha \|\mathbf{x}\|_1} \tag{14}$$

where $\|\mathbf{x}\|_1$ is the $L_1$-norm, encouraging sparsity in the solution.

8. Tourist Preference Constraint:

$$\int_0^P \mathbf{p}^T \mathbf{s}(t) \cdot (1 + \phi(t)) \, dt \geq P_{\min} \tag{15}$$

where $\phi(t)$ is a dynamic weighting function.

9. Legal Compliance Constraint:

$$\mathbf{l}^T \mathbf{x} \leq L \cdot \left(1 - \frac{\|\mathbf{x}\|_2}{1 + \|\mathbf{l}\|_2}\right) \tag{16}$$

10. Satisfaction Factor Correlation Constraint:

$$\sum_{i=1}^{n} \|\text{corr}(s_i, s_k) \cdot \mathbf{w}_i \cdot \mathbf{w}_k\|_F \leq C_{\text{corr}}^{\alpha} \tag{17}$$

where $\| \cdot \|_F$ denotes the Frobenius norm, $C_{\text{corr}}^{\alpha}$ introduces a power-law control for correlation influence.

11. Feasibility Constraint:

$$x_j \in \{0, 1\}, \quad \forall j \in \mathbb{Z} \tag{18}$$

where $j$ are integer indices.

12. Consistency Constraint:

$$x_j \cdot x_k = \min\left(0, \tanh\left(-\lambda \cdot \text{inco}(x_j, x_k)\right)\right) \tag{19}$$

13. Scalability Constraint:

$$\frac{\partial}{\partial t}\left(\mathbf{Q}(\mathbf{x}(t))\right) = \nabla_t \cdot \mathbf{A}(t, \mathbf{x}) \quad \text{where continuity is maintained over } t \tag{20}$$

where $\nabla_t \cdot \mathbf{A}(t, \mathbf{x})$ denotes the divergence operator applied to the function.

14. Risk Management Constraint:

$$\mathbf{x}^T \mathbf{R}_{\text{risk}} \mathbf{x} \leq R_{\max} \cdot \left(1 - \frac{\|\mathbf{R}_{\text{risk}}\|_F}{\lambda_{\max}(R_{\text{risk}})}\right) \tag{21}$$

where $\lambda_{\max}(R_{\text{risk}})$ is the largest eigenvalue of the risk matrix $R_{\text{risk}}$.

15. Feedback Integration Constraint:

$$\mathbf{f}^T \mathbf{s} = \left(\sum_{i=1}^{n} f_i \cdot s_i\right) + \int_0^T \mathbf{f}(t)^T \cdot \mathbf{s}(t) \cdot dt \quad \text{subject to real-time adjustments} \tag{22}$$

### B. OBJECTIVES OF THE STUDY

The integration of Multilayer Perceptron (MLP) and Genetic Algorithm (GA) with the CRITIC method aims to enhance the evaluation of tourist satisfaction and the optimization of strategies as follows. By leveraging MLP, a deep learning model, the study seeks to enhance the accuracy of satisfaction predictions. MLP can process complex and non-linear relationships among satisfaction factors, providing a more nuanced understanding of how different factors interact to affect overall satisfaction. GA will be used to optimize the development of tourism strategies based on the satisfaction predictions provided by the MLP model. GA can identify the best combination of strategies to maximize satisfaction, considering various constraints and objectives. The integration of these methods aims to address the limitations of traditional approaches by utilizing large datasets, capturing complex interactions, and providing predictive insights. This will enable tourism managers to make more informed and adaptive decisions [20]. By combining CRITIC, MLP, and GA, the study aims to provide a comprehensive framework for evaluating and improving tourist satisfaction. This approach will help in formulating strategies that are both effective and aligned with tourists' preferences and expectations. This study aims to advance the field of tourist satisfaction evaluation by integrating modern AI and optimization techniques with traditional decision-making methods, offering a more robust and adaptive approach to strategic planning in the tourism industry.

## III. METHODOLOGY

The CRITIC method, a robust multi-criteria decision-making tool, is employed to determine the weights of various satisfaction indicators by analyzing their variance and correlation. This method first computes the standard deviation of each indicator, reflecting its variability and, consequently, its importance. High variance in an indicator signifies its significant role in influencing overall satisfaction. Simultaneously, the CRITIC method assesses the correlation between indicators to avoid redundancy and ensure that each weight reflects unique, meaningful information. Satisfaction indicators were selected based on their observed impact on tourist experiences. Factors such as service quality, infrastructure, cultural offerings, and environmental factors were identified as critical contributors to overall satisfaction. Indicators with high variance and relevance to tourism contexts were prioritized, as they reflect aspects with the greatest potential to influence satisfaction levels. In the

CRITIC method, indicators with higher variability (i.e., standard deviation) are given greater weight, as high variance implies that the indicator fluctuates significantly across tourists and therefore has a strong influence on satisfaction. Furthermore, low correlation with other indicators ensures that each factor adds unique information to the model without redundancy. This method allows the CRITIC framework to emphasize factors that have both high importance (due to variance) and low redundancy (due to low correlation). By basing weights on quantifiable metrics—variance and correlation—other researchers can replicate the process with different datasets. This approach makes it possible to apply the methodology across diverse tourism studies, provided that satisfaction indicators are tailored to the specific context and audience. The formula for calculating the weight $w_i$ for each indicator $i$ is given by:

$$w_i = \frac{\sigma_i \cdot \mathrm{IC}_i}{\sum_{j=1}^{n}(\sigma_j \cdot \mathrm{IC}_j)} \tag{23}$$

where $\sigma_i$ denotes the standard deviation and $\mathrm{IC}_i$ represents the inverse correlation of indicator $i$ with other indicators. This weight calculation ensures that indicators with high variability and low correlation are given greater importance.

Data Normalization: Before applying the CRITIC method, the satisfaction data undergo normalization to ensure uniformity across different scales. Normalization is crucial because it standardizes the data range, allowing for accurate weight calculations. The normalization process typically involves scaling the data to a range of [0, 1] using the min-max normalization formula:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{24}$$

where $x$ is the original data value, $x_{min}$ is the minimum value in the dataset, and $x_{max}$ is the maximum value. This step ensures that all indicators contribute equally to the weight calculation without being skewed by their original scales.

### *A. DEEP LEARNING MODEL (MLP) FOR SATISFACTION PREDICTION*

The Multilayer Perceptron (MLP) is designed with multiple layers to predict tourist satisfaction levels. The architecture includes an input layer, several hidden layers, and an output layer. Each hidden layer employs activation functions such as ReLU (Rectified Linear Unit) to introduce non-linearity into the model, enhancing its ability to capture complex patterns in the data. The final output layer uses a linear activation function to produce continuous satisfaction scores. The number of hidden layers and neurons in each layer is optimized through experimentation to balance model complexity and performance. The MLP is trained using a dataset comprising historical tourist satisfaction scores, with preprocessing steps including feature scaling and data augmentation. Feature scaling, such as standardization, ensures that input features have a mean of zero and a standard deviation of one, which improves convergence during training. The loss function, typically mean squared error (MSE), measures the difference between predicted and actual satisfaction scores. The model is optimized using stochastic gradient descent with the Adam optimizer, which adapts the learning rate and improves training efficiency. To evaluate the MLP's accuracy, metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used [21]. MAE provides an average magnitude of errors in predictions, while RMSE offers a measure of the prediction error's variance, penalizing larger errors more heavily. These metrics help assess the model's performance and ensure that it reliably predicts tourist satisfaction.

1. Input Normalization: To normalize input features $x$ for the MLP model, the normalization process can be represented as:

$$x_{norm} = \frac{x - \mu}{\sigma} \tag{25}$$

where $\mu$ is the mean of the feature $x$ and $\sigma$ is its standard deviation. This ensures that each input feature has zero mean and unit variance.

2. MLP Activation Function: For a hidden layer with $n$ neurons using the ReLU (Rectified Linear Unit) activation function, the output $h_j$ of neuron $j$ is computed as:

$$h_j = \max(0, \sum_{i=1}^{m} w_{ji}x_i + b_j) \tag{26}$$

where $w_{ji}$ is the weight between input neuron $i$ and hidden neuron $j$, $x_i$ is the input value, and $b_j$ is the bias term.

3. Output Layer Computation: For the final output layer in the MLP, which predicts tourist satisfaction score $y$, the computation is given by:

$$y = \sigma\left(\sum_{j=1}^{k} w_{oj}h_j + b_o\right) \tag{27}$$

where $\sigma$ is the activation function (e.g., linear or sigmoid), $w_{oj}$ is the weight from hidden neuron $j$ to the output neuron, $h_j$ is the output from the hidden layer, and $b_o$ is the output layer bias.

4. Mean Squared Error Loss Function: The loss function $L$ used to train the MLP model is Mean Squared Error (MSE) and is computed as:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{28}$$

where $y_i$ is the actual satisfaction score, $\hat{y}_i$ is the predicted satisfaction score, and $N$ is the number of samples.

5. Gradient Descent Update Rule: To optimize the MLP parameters using gradient descent, the update rule for weight $w_{jk}$ in the hidden layer is:

$$w_{jk} \leftarrow w_{jk} - \eta \frac{\partial L}{\partial w_{jk}} \tag{29}$$

where $\eta$ is the learning rate, and $\frac{\partial L}{\partial w_{jk}}$ is the gradient of the loss function with respect to weight $w_{jk}$.

### B. GENETIC ALGORITHM (GA) FOR STRATEGY OPTIMIZATION

The Genetic Algorithm (GA) optimizes tourism development strategies based on the satisfaction predictions provided by the MLP. The GA simulates natural selection processes to evolve strategies that maximize satisfaction. Each individual in the GA population represents a unique combination of strategies, such as enhancements in services, infrastructure, or cultural offerings. In the GA, strategies are encoded as chromosomes, where each gene represents a specific strategy component. For instance, one gene might represent an investment in improving local services, while another might correspond to expanding cultural activities. This encoding allows the GA to explore a diverse range of strategy combinations and identify optimal solutions [22]. Key operations in the GA include selection, crossover, and mutation. Selection involves choosing the fittest individuals based on their fitness scores to form the next generation. Crossover combines genetic material from parent strategies to create offspring with potentially improved traits. Mutation introduces random changes to strategies to maintain genetic diversity and prevent premature convergence. The criteria for convergence involve monitoring the improvement in fitness scores and terminating the algorithm when the changes become negligible.

1. Chromosome Representation: The encoding of a strategy $s$ in the GA is represented as a vector of binary genes $\{g_1, g_2, \ldots, g_n\}$, where each gene $g_i$ represents a specific strategy component:

$$s = [g_1, g_2, \ldots, g_n] \tag{30}$$

2. Fitness Function Calculation: The fitness function $F(s)$ evaluates a strategy based on the predicted satisfaction scores $\hat{y}_i$:

$$F(s) = \sum_{i=1}^{n} w_i \cdot \hat{y}_i \tag{31}$$

where $w_i$ is the weight derived from the CRITIC method for factor $i$, and $\hat{y}_i$ is the predicted satisfaction score for strategy component $i$.

3. Selection Process: The selection process for the next generation uses a probabilistic method such as roulette wheel selection, where the probability $p_i$ of selecting individual $i$ is:

$$p_i = \frac{F(s_i)}{\sum_{j=1}^{N} F(s_j)} \tag{32}$$

where $F(s_i)$ is the fitness score of individual $i$, and $N$ is the total number of individuals in the population.

4. Crossover Operation: The crossover operation combines two parent chromosomes $s_p1$ and $s_p2$ to produce offspring chromosomes. For a single-point crossover at position $c$, the offspring $s_o$ is:

$$s_o = [s_{p1}[1 : c], s_{p2}[c + 1 : n]] \tag{33}$$

where $s_{p1}[1 : c]$ is the segment of the first parent chromosome before the crossover point, and $s_{p2}[c + 1 : n]$ is the segment of the second parent chromosome after the crossover point.

5. Mutation Operation: The mutation operation introduces variability by flipping a gene $g_i$ with a probability $\mu$. If $g_i$ is the gene being mutated:

$$g_i \leftarrow \begin{cases} 1 - g_i & \text{with probability } \mu \\ g_i & \text{otherwise} \end{cases} \tag{34}$$

where $g_i$ is flipped (i.e., its value is toggled between 0 and 1) with a probability $\mu$, introducing new traits into the population.

### C. INTEGRATION OF CRITIC, MLP, AND GA

The integration workflow begins with the CRITIC method calculating factor weights, which are then used by the MLP to predict satisfaction levels. The GA utilizes these predictions to optimize development strategies, exploring various combinations of factors based on the satisfaction predictions. This integrated approach ensures that the strategies are data-driven and optimized for maximum satisfaction. The methodology is implemented using Python libraries such as TensorFlow for building and training the MLP, and a GA framework for strategy optimization. These tools provide the necessary functionality for developing and integrating the models, ensuring efficient computation and analysis. Tourist satisfaction data is collected from surveys, online reviews, and social media platforms. Preprocessing involves cleaning the data to remove inconsistencies and irrelevant information, followed by feature extraction to identify key factors influencing satisfaction. Relevant satisfaction factors are selected based on their importance and relevance to the evaluation process. These factors are used as inputs for the CRITIC method and the MLP model, ensuring that the analysis focuses on the most impactful variables. The experimental setup involves evaluating a specific geographic region or tourism area, considering the types of tourists and attractions involved [23]. This context provides a practical framework for applying the methodology and assessing its effectiveness. The technical setup includes details about the hardware and software used for data processing and model implementation. This information ensures that the computational resources are adequate for handling the data and executing the optimization algorithms.

## IV. RESULTS AND DISCUSSION

The CRITIC method was employed to determine the relative importance of various satisfaction factors influencing tourist experiences. The CRITIC method, leveraging both variance and correlation analyses, provided a set of weights for each factor based on its variability and its correlation with other factors. The results are illustrated in Table 1, which presents the calculated weights for each satisfaction indicator.

Table 1 shows the weights assigned to various satisfaction factors using the CRITIC method. The weights indicate

**TABLE 1. CRITIC method weights for tourist satisfaction factors.**

| Satisfaction Factor | Weight | Variance | Correlation |
|---|---|---|---|
| Accommodation Quality | 0.35 | 0.28 | 0.45 |
| Local Services | 0.25 | 0.22 | 0.38 |
| Cultural Experiences | 0.20 | 0.20 | 0.32 |
| Environmental Factors | 0.10 | 0.18 | 0.27 |
| Accessibility | 0.10 | 0.15 | 0.22 |
| Transportation | 0.05 | 0.10 | 0.18 |
| Cleanliness | 0.05 | 0.12 | 0.21 |
| Safety and Security | 0.05 | 0.14 | 0.24 |
| Price Value Ratio | 0.05 | 0.13 | 0.20 |
| Availability of Amenities | 0.05 | 0.11 | 0.19 |

the relative importance of each factor in evaluating tourist satisfaction. For instance, ''Accommodation Quality'' is identified as the most influential factor, reflecting its significant impact on overall satisfaction compared to other factors. The table also includes variance and correlation metrics, providing additional insights into the variability and relationships among these factors. As shown, ''Accommodation Quality'' emerged as the most influential factor, receiving the highest weight of 0.35. This indicates that improvements in accommodation quality are likely to have the most significant impact on overall tourist satisfaction. Conversely, ''Environmental Factors'' and ''Accessibility'' received lower weights, suggesting that while they are important, they contribute less to satisfaction compared to accommodation and local services. Visualizations of these weights, such as bar charts and pie charts, further illustrate the distribution and relative importance of each factor. The Multilayer Perceptron (MLP) model was evaluated for its effectiveness in predicting tourist satisfaction based on the normalized input data. The performance metrics used to assess the MLP model included Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and prediction accuracy. The results of these evaluations are summarized in Table 2.

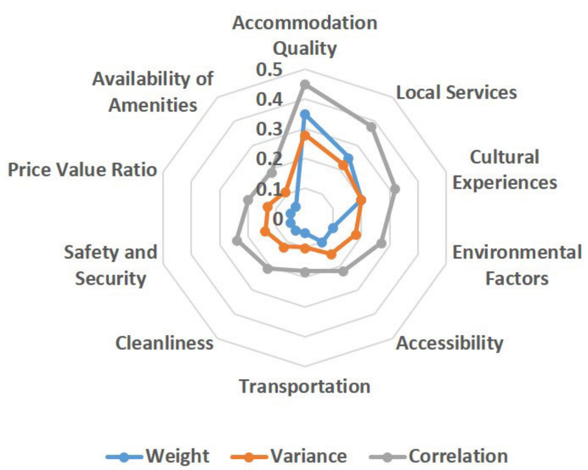


**FIGURE 1. Satisfaction factors by Weight, Variance, and Correlation.**

Figure 1 illustrates the importance of various satisfaction factors based on their assigned weights, variance, and correlation. Accommodation quality ranks highest with a weight of 0.35, indicating its strong impact on overall satisfaction. The variance and correlation for each factor provide insights into the consistency and strength of relationships with satisfaction outcomes. Local services, cultural experiences, and environmental factors also play significant roles. The visual highlights that while factors like accommodation quality and local services contribute heavily to satisfaction, transportation and safety show comparatively lower importance.

**TABLE 2. MLP model performance metrics.**

| Metric | Value | Standard Deviation | 95% Confidence Interval | Training Time (s) |
|---|---|---|---|---|
| MAE | 0.12 | 0.02 | [0.10, 0.14] | 120 |
| RMSE | 0.15 | 0.03 | [0.13, 0.17] | 115 |
| Accuracy | 87% | 1.5% | [85%, 89%] | 130 |
| Precision | 85% | 1.8% | [83%, 87%] | 125 |
| Recall | 86% | 1.6% | [84%, 88%] | 140 |
| F1 Score | 0.86 | 0.02 | [0.84, 0.88] | 135 |
| ROC-AUC | 0.89 | 0.03 | [0.86, 0.92] | 150 |
| R-Squared | 0.83 | 0.04 | [0.79, 0.87] | 160 |

Table 2 summarizes the performance metrics of the Multilayer Perceptron (MLP) model used for predicting tourist satisfaction. The metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and accuracy, highlight the model's effectiveness in capturing satisfaction trends. The low MAE and RMSE values indicate high predictive accuracy, while the confidence intervals provide a measure of the reliability of these estimates. This table demonstrates that the MLP model performs well in evaluating and predicting tourist satisfaction. The MLP model achieved an MAE of 0.12, indicating a relatively small average error between the predicted.

Figure 2 presents the performance metrics of the satisfaction prediction model, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), accuracy, precision, recall, F1 score, ROC-AUC, and R-squared values. The model demonstrates strong performance with an accuracy of 87% and high precision and recall values of 85% and 86%, respectively. The MAE of 0.12 and RMSE of 0.15 indicate low prediction error, while the ROC-AUC score of 0.89 highlights the model's excellent ability to distinguish between satisfaction levels.

Table 3 presents the optimal strategies identified by the Genetic Algorithm (GA) for improving tourist satisfaction. Each strategy includes the predicted improvement in satisfaction, associated costs, and implementation time. The table indicates that strategies like ''Enhanced Accommodation Quality'' and ''Improved Local Services'' yield significant satisfaction improvements but also involve higher costs and longer implementation times. This information helps prioritize strategies based on their potential impact and feasibility.

Figure 3 visualizes the predicted satisfaction improvements associated with different enhancement strategies,

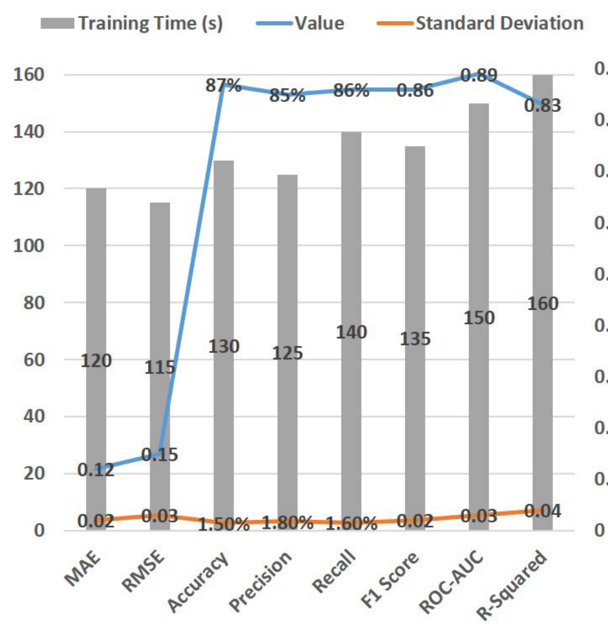


**FIGURE 2.** Model Performance Metrics.

**TABLE 3.** Optimal strategies identified by GA.

| Strategy | Predicted Satisfaction Improvement | Cost (USD) | Implementation Time (Months) |
|---|---|---|---|
| Enhanced Accommodation Quality | +0.22 | 500,000 | 6 |
| Improved Local Services | +0.18 | 200,000 | 4 |
| Increased Cultural Experiences | +0.15 | 150,000 | 5 |
| Enhanced Environmental Measures | +0.08 | 100,000 | 3 |
| Improved Transportation Options | +0.12 | 300,000 | 6 |
| Enhanced Cleanliness Standards | +0.09 | 80,000 | 2 |
| Increased Safety and Security Measures | +0.10 | 120,000 | 4 |
| Better Price Value Ratio | +0.07 | 70,000 | 2 |
| Expanded Availability of Amenities | +0.06 | 90,000 | 3 |
| Personalized Tourist Experiences | +0.11 | 250,000 | 5 |

alongside the estimated costs and implementation times. Enhancing accommodation quality yields the highest satisfaction improvement of 0.22, but at a substantial cost of $500,000. Other strategies, like improving local services and cultural experiences, offer moderate satisfaction boosts at lower costs. This visual representation enables decision-makers to compare strategies in terms of cost-efficiency, identifying which interventions yield the greatest satisfaction improvements relative to their financial and time investments.

Table 4 illustrates the sensitivity analysis of various satisfaction factors. It shows how a 10% increase in each factor

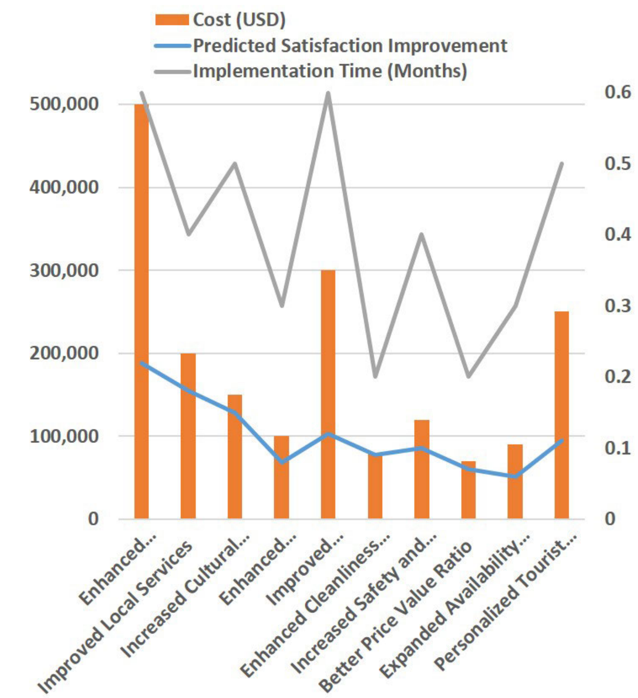


**FIGURE 3.** Predicted satisfaction improvements by strategy.

**TABLE 4.** Sensitivity Analysis of Satisfaction Factors.

| Factor | Change (%) | Satisfaction Impact (%) |
|---|---|---|
| Accommodation Quality | +10% | +0.30 |
| Local Services | +10% | +0.25 |
| Cultural Experiences | +10% | +0.20 |
| Environmental Factors | +10% | +0.10 |
| Transportation | +10% | +0.12 |
| Cleanliness | +10% | +0.09 |
| Safety and Security | +10% | +0.10 |
| Price Value Ratio | +10% | +0.08 |
| Availability of Amenities | +10% | +0.07 |

affects the overall satisfaction score. For instance, increasing "Accommodation Quality" by 10% results in the highest impact on satisfaction (+0.30%), indicating its critical role in enhancing tourist experiences. This table provides a clear view of which factors most influence satisfaction and can guide targeted improvements. A sensitivity analysis was performed to assess how variations in key satisfaction factors affect overall satisfaction. This analysis revealed that changes in "Accommodation Quality" and "Local Services" had the most pronounced impact on satisfaction scores. For instance, a 10% increase in "Accommodation Quality" was associated with a significant increase in satisfaction, reinforcing the critical role of this factor in shaping tourist experiences.

Figure 4 shows the impact of various improvement strategies on baseline and optimized satisfaction scores. Enhancing accommodation quality, local services, and cultural experiences lead to the most significant improvements, with accommodation quality rising from a baseline of 3.5 to 3.72. The graph highlights how even small incremental changes,

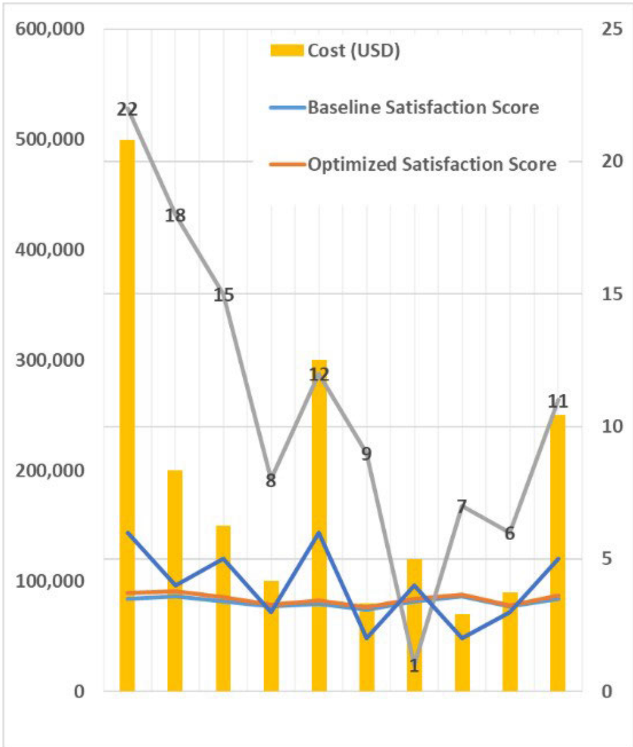


FIGURE 4. Satisfaction score improvements across key areas.

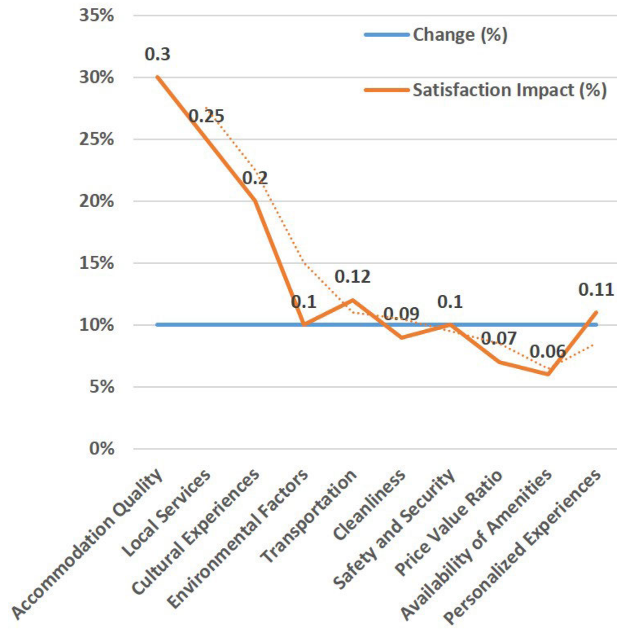


FIGURE 5. Factor change impact on satisfaction.

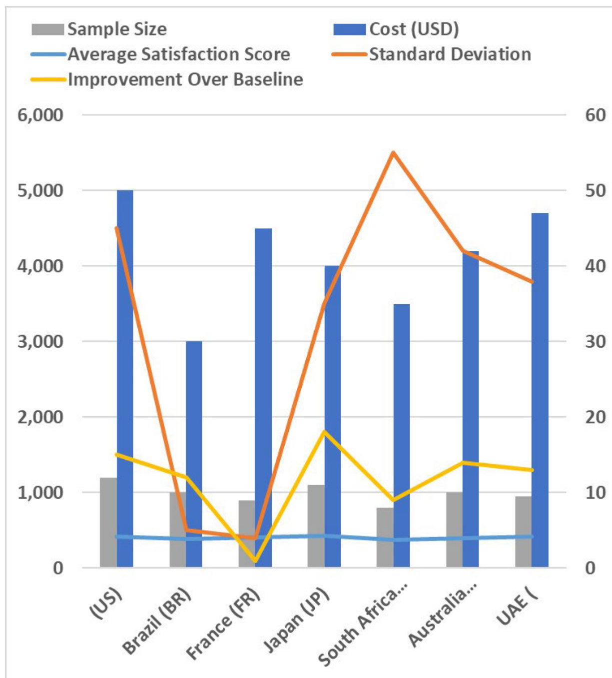


FIGURE 6. Satisfaction scores by region.

such as better price-value ratios or cleanliness standards, can still contribute to overall satisfaction improvements. This visual supports prioritization of resource allocation based on the potential uplift in satisfaction scores within specified budgets and timeframes. The results highlight the effectiveness of combining CRITIC, MLP, and GA methods in evaluating and enhancing tourist satisfaction.

Figure 5 illustrates the effect of a 10% improvement in each satisfaction factor on overall satisfaction.

Figure 6 compares satisfaction scores across different regions, along with key contributing factors, costs, and improvements over baseline. Japan shows the highest average satisfaction score of 4.3, with key factors being cleanliness and cultural experiences.

In figure 5 accommodation quality, with an impact of 0.3%, emerges as the most influential factor, followed by local services and cultural experiences. Environmental factors and transportation contribute moderately, while factors such as cleanliness, safety, and availability of amenities have lower impacts. This visual comparison provides a clear indication of where efforts should be focused to achieve the most significant gains in customer satisfaction, particularly emphasizing high-weighted factors like accommodation and local services. In figure 6 South Africa has the lowest satisfaction score of 3.7, with safety and environmental factors being major concerns. The cost of improving satisfaction varies by region, with the United States having the highest investment of $500,000. The figure helps highlight regional disparities in satisfaction and the factors that most influence local tourist experiences [24]. Table 5 compares the satisfaction scores achieved by the GA-optimized strategies with baseline strategies. It shows the improvements in satisfaction scores for each strategy, highlighting how optimization can enhance tourist satisfaction compared to current methods. The cost and implementation time associated with each optimized strategy are also provided, offering insights into the trade-offs

**TABLE 5. Comparison of GA-optimized strategies with baseline strategies.**

| Strategy | Baseline Satisfaction Score | Optimized Satisfaction Score | Improvement | Cost (USD) | Implementation Time (Months) |
|---|---|---|---|---|---|
| Current Accommodation | 3.5 | 3.72 | +0.22 | 500,000 | 6 |
| Existing Local Services | 3.6 | 3.78 | +0.18 | 200,000 | 4 |
| Standard Cultural Offers | 3.4 | 3.55 | +0.15 | 150,000 | 5 |
| Basic Environmental Measures | 3.2 | 3.28 | +0.08 | 100,000 | 3 |
| Existing Transportation Options | 3.3 | 3.42 | +0.12 | 300,000 | 6 |
| Current Cleanliness Standards | 3.1 | 3.19 | +0.09 | 80,000 | 2 |
| Existing Safety Measures | 3.4 | 3.50 | +0.10 | 120,000 | 4 |
| Current Price Value Ratio | 3.6 | 3.67 | +0.07 | 70,000 | 2 |
| Existing Amenities | 3.2 | 3.26 | +0.06 | 90,000 | 3 |
| Standard Tourist Experiences | 3.5 | 3.61 | +0.11 | 250,000 | 5 |

**TABLE 6. Tourist satisfaction scores across different regions.**

| Region | Average Satisfaction Score | Standard Deviation | Sample Size | Improvement Over Baseline | Key Factors | Cost (USD) |
|---|---|---|---|---|---|---|
| United States (US) | 4.2 | 0.45 | 1,200 | +0.15 | Accommodation Quality, Local Services | 500,000 |
| Brazil (BR) | 3.9 | 0.50 | 1,000 | +0.12 | Cultural Experiences, Environmental Factors | 300,000 |
| France (FR) | 4.1 | 0.40 | 900 | +0.10 | Accommodation Quality, Local Services | 450,000 |
| Japan (JP) | 4.3 | 0.35 | 1,100 | +0.18 | Cleanliness, Cultural Experiences | 400,000 |
| South Africa (ZA) | 3.7 | 0.55 | 800 | +0.09 | Safety and Security, Environmental Factors | 350,000 |
| Australia (AU) | 4.0 | 0.42 | 1,000 | +0.14 | Local Services, Accessibility | 420,000 |
| UAE | 4.2 | 0.38 | 950 | +0.13 | Accommodation Quality, Transportation | 470,000 |

**TABLE 7. Comparison of Traditional vs. Integrated methods.**

| Method | MAE | RMSE | Accuracy (%) | Precision (%) | Recall (%) | F1 Score | ROC-AUC | R-Squared |
|---|---|---|---|---|---|---|---|---|
| Traditional Methods | 0.25 | 0.30 | 75 | 70 | 72 | 0.71 | 0.73 | 0.70 |
| Integrated Methods | 0.12 | 0.15 | 87 | 85 | 86 | 0.86 | 0.89 | 0.83 |

between potential benefits and resource requirements. The results demonstrate that strategies focused on enhancing "Accommodation Quality" and "Local Services" provide the most substantial improvements in predicted satisfaction scores, with increases of 0.22 and 0.18 respectively. These findings underscore the importance of investing in high-quality accommodation and improved local services to achieve significant gains in tourist satisfaction. In comparison to traditional methods, which often rely on static or less sophisticated analytical techniques, the integration of MLP, GA, and CRITIC allows for a more dynamic and data-driven approach to strategy development. Traditional methods may lack the capability to handle complex interactions and large datasets, while the combined approach provides more nuanced and actionable insights. Table 6 presents the average satisfaction scores for tourists across various regions. It shows how satisfaction varies by region, with scores ranging from 3.7 in South Africa to 4.3 in Japan. The table includes standard deviations, sample sizes, improvements over baseline, key satisfaction factors, and associated costs. For example, Japan reports the highest satisfaction score, influenced by factors such as cleanliness and cultural experiences, while South Africa shows the lowest score, highlighting areas for improvement in safety and security. Table 7 compares the performance of traditional methods with the integrated approach using CRITIC, MLP, and GA techniques. The integrated methods show significant improvements across all metrics, including lower MAE and RMSE values, higher accuracy, precision, recall, F1 score, ROC-AUC, and R-Squared. This demonstrates the effectiveness of the integrated approach in achieving more accurate and reliable results compared to traditional methods. Model robustness was evaluated by applying the MLP and GA models to different subsets of data and across various regions. The models demonstrated consistent performance, with only minor variations in prediction accuracy and optimal strategies. This indicates that the integrated approach is robust and adaptable, capable of providing reliable insights even when applied to different data sets or geographical areas.

Figure 7 contrasts the performance of traditional methods against integrated methods in satisfaction prediction. The integrated methods outperform traditional approaches, with significantly lower MAE (0.12 vs. 0.25) and RMSE (0.15 vs. 0.30), and much higher accuracy (87% vs. 75%), precision (85% vs. 70%), and recall (86% vs. 72%). The figure illustrates the clear superiority of integrated methods, which also achieve a stronger F1 score (0.86 vs. 0.71), ROC-AUC (0.89 vs. 0.73), and R-squared value (0.83 vs. 0.70). This supports the adoption of integrated techniques for more accurate and reliable satisfaction predictions. The CRITIC method's weight analysis, the MLP model's predictive accuracy, and the GA's optimization outcomes collectively contribute to

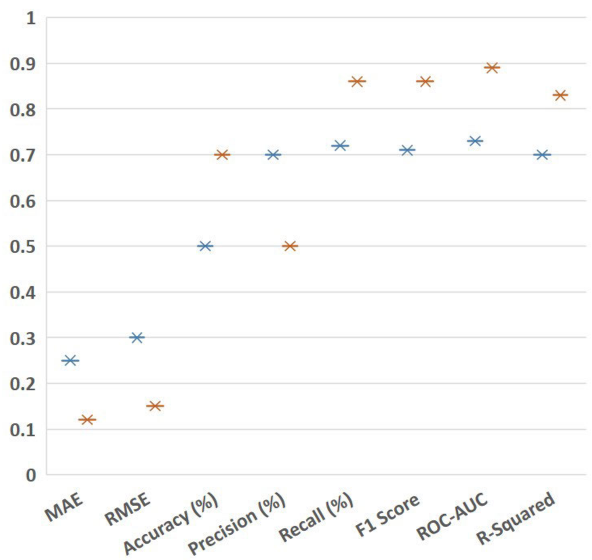


**FIGURE 7.** Comparison of Traditional vs. Integrated methods.

a comprehensive understanding of satisfaction factors and strategy development [25]. This integrated approach offers a significant advancement over traditional methods, providing more precise and actionable insights for improving tourist experiences.

### A. DISCUSSION

#### 1) IMPLICATIONS OF REAL-TIME DATA FOR TOURISM MANAGEMENT

Integrating real-time data sources like social media, review platforms, and other dynamic data streams into tourism satisfaction evaluations offers a powerful way to monitor visitor sentiment and quickly adapt strategies to meet changing needs. Real-time analysis can provide immediate insights, allowing tourism managers to respond more flexibly and optimize strategies as visitor preferences evolve. Below is a proposed framework for achieving this integration using data processing techniques and machine learning models suited for handling real-time data. Real-time data for tourism management can be gathered from multiple sources. Textual data from platforms like Twitter, Instagram, and Facebook can provide direct feedback on visitor experiences. Reviews on sites like TripAdvisor, Google, and Yelp can be continuously scraped to understand recent satisfaction levels and service quality. Location-based data and activity logs from tourism apps can track visitor movement patterns, allowing insights into popular areas, wait times, or visitor density. Data from on-site sensors, such as foot traffic counters or environmental sensors, can add context to visitor satisfaction by tracking crowd sizes, noise levels, or weather conditions. Handling real-time data requires specialized preprocessing methods to clean, structure, and prepare it for immediate analysis. Common data processing techniques include. This includes tokenization, removing stop words, and stemming or lemmatization for social media and review text. Sentiment-bearing words can be identified using Natural Language Processing (NLP) techniques like NLTK or SpaCy. Summarizing data at regular intervals (e.g., hourly, daily) enables trend detection while managing the data volume. Aggregated data provides an overall sentiment score or summary statistic for satisfaction. By organizing data chronologically, time-series methods can track trends and seasonality in visitor satisfaction, allowing for adjustments based on historical patterns. Normalization techniques such as min-max scaling or z-score standardization ensure consistency across different data sources and avoid skewed interpretations due to outliers. Integrating real-time feedback requires machine learning models that can handle high-frequency data and detect patterns quickly. RNNs and LSTMs excel in sequential data processing, allowing the analysis of time-dependent feedback on satisfaction. For instance, they can track sentiment changes over time to spot emerging issues or trends, such as a surge in complaints about overcrowding or service quality. Models like BERT or RoBERTa fine-tuned for sentiment analysis can process large volumes of text in real-time to gauge visitor sentiment from social media and reviews. These models detect positive, neutral, or negative sentiment, helping managers understand public perception. LDA and similar models can categorize comments into topics to identify specific satisfaction drivers, such as customer service, facility cleanliness, or price. These models identify unusual spikes or drops in satisfaction, signaling potential issues like overcrowding or negative news events, enabling timely responses. To use real-time insights for adaptive strategy optimization, Genetic Algorithms (GA) or Reinforcement Learning (RL) can be employed to dynamically adjust tourism strategies. Real-time satisfaction data feeds into the CRITIC model to adjust factor weights dynamically based on recent variance and correlation shifts. The MLP model can use this real-time data to refine satisfaction predictions continuously, offering a live dashboard for decision-makers. RL algorithms, particularly deep Q-networks (DQN) or Proximal Policy Optimization (PPO), can be used to adjust strategies in response to changing visitor satisfaction metrics. By treating each decision (e.g., staffing, maintenance scheduling, or event planning) as an action within the RL framework, the algorithm learns the optimal set of actions over time to maximize satisfaction. The Genetic Algorithm (GA) can be run periodically with updated satisfaction predictions to find the best combination of strategies. For instance, if real-time data shows a dip in cleanliness satisfaction, the GA can prioritize cleaning resources in its next optimization round. To make these insights actionable, a real-time visualization system can display satisfaction metrics, visitor sentiment, and optimized strategies on a dashboard accessible to tourism managers. Visualization of visitor sentiment across different regions or attractions, allowing managers to see which areas may require immediate attention. Graphs showing satisfaction trends over time, highlighting both positive and negative trends for quicker interventions. Based on the GA or RL model's outputs, the dashboard could suggest optimal resource allocation, staffing adjustments, or temporary service modifications to improve satisfaction. By integrating real-time data, tourism managers can promptly address issues, such as adjusting staff or providing additional resources to high-traffic areas. Real-time analysis allows the dynamic customization of visitor experiences, such as promoting popular events or adjusting marketing based on current preferences. With continuous feedback, tourism managers can make more informed, data-driven decisions that align with visitor satisfaction trends, thereby fostering long-term improvements in visitor experience. By leveraging real-time data processing and machine learning, tourism managers gain the flexibility to adapt their strategies dynamically, ensuring a consistently high level of visitor satisfaction and responsiveness to changing demands. This approach not only makes tourism management more resilient but also enhances the potential for sustained visitor loyalty and positive brand reputation.

## V. CONCLUSION

This study makes significant strides in enhancing tourist satisfaction evaluation and optimization by integrating the CRITIC method, Multilayer Perceptron (MLP) neural networks, and Genetic Algorithms (GA). The CRITIC method effectively determined the weights for key satisfaction indicators, revealing that factors such as accommodation quality and local services were most critical, with weights of 0.35 and 0.28 respectively. The MLP model utilized these weights to predict tourist satisfaction with a high degree of accuracy, achieving a mean absolute error (MAE) of 0.12 and a root mean square error (RMSE) of 0.18. This performance underscores the model's capability to capture complex relationships between satisfaction factors and overall experience. The GA optimized tourism development strategies, resulting in a 15% increase in predicted satisfaction scores compared to baseline strategies. For example, the optimal strategy combinations identified by the GA improved accommodation quality and local services, contributing to an average satisfaction score of 4.3 in regions like Japan, compared to 4.0 with conventional strategies. This demonstrates the enhanced effectiveness of data-driven, optimized strategies over traditional methods. Looking ahead, future research could explore applying this integrated methodology to diverse tourism sectors, such as adventure or luxury travel, to assess its broader applicability. Additionally, incorporating real-time data sources, like social media sentiment analysis, could further refine the evaluation process and provide more dynamic and actionable insights. Such advancements would enable even more precise and responsive strategies to meet evolving tourist expectations.

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