

Hybrid Emotion and Satisfaction-Aware Fuzzy Inference System (ES-FIS) for Predicting Tourist Revisit Intention

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ABSTRACT – Tourist revisit intention is influenced by both cognitive evaluations and emotional experiences; however, existing models typically treat these factors independently and rely on precise numerical inputs that may not reflect the subjective nature of travel perception. This study develops a Hybrid Emotion–Satisfaction Fuzzy Inference System (ES-FIS) designed to model such ambiguity while maintaining interpretability through linguistic rules. The model integrates six structured satisfaction dimensions from 415 Thai visitors to Japan with affective polarity extracted from 20,491 TripAdvisor reviews via a probabilistic mapping approach. All variables were transformed into fuzzy linguistic terms and processed using a Mamdani-type inference engine to generate both a continuous revisit score and categorical outputs. Empirical evaluation indicates that the ES-FIS achieves strong predictive performance (Accuracy: 0.78, F1-score: 0.74) with results aligned with ground-truth Likert ratings ($r = 0.71$; RMSE = 0.48). Furthermore, PCA-based clustering reveals three distinct cognitive–affective traveler segments. These findings suggest that combining satisfaction and emotional indicators provides a more comprehensive representation of revisit intention than relying on either component alone. The study contributes to an explainable AI (XAI) framework that captures the inherent imprecision of tourist perception and offers practical value for service personalization and CRM-oriented segmentation in tourism analytics.

KEY WORDS --Fuzzy inference system, Explainable AI, Sentiment analysis, Affective signals, Revisit intention, Tourism analytics, CRM

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1. Introduction

Tourist revisit intention is widely regarded as a critical indicator of destination loyalty and long-term tourism sustainability. Repeat visitation not only contributes to stable revenue streams but also enhances brand reputation through positive word-of-mouth and reduces marketing expenditure associated with attracting first-time visitors. As international competition intensifies, understanding the multifaceted determinants of revisit intention has

become a strategic priority for tourism stakeholders. Recent studies have highlighted that existing models of revisit intention remain limited because they treat rational satisfaction and emotional experience as separate predictors, despite evidence showing that tourist behavior is shaped by the interaction of both cognitive and affective factors [1].

Related Work: Traditional frameworks such as Ajzen's Theory of Planned Behavior (TPB) and Oliver's Expectation–Confirmation Theory (ECT) have substantially shaped the understanding of revisit

intention. TPB posits that intention is driven by attitudes, subjective norms, and perceived behavioral control [2], while ECT highlights that satisfaction arises from the confirmation of prior expectations, thereby influencing loyalty behaviors [3]. Theory emphasizes rational cognitive evaluations, while sentiment-analysis research demonstrates that emotional polarity extracted from user-generated content significantly influences satisfaction, destination image, and loyalty behaviors. Moreover, prior applications of fuzzy logic within tourism mainly rely on structured survey data and seldom incorporate unstructured emotional information, thereby overlooking important affective determinants of behavioral intention.

With the proliferation of user-generated content (UGC) on platforms such as TripAdvisor, tourists increasingly articulate emotions—such as joy, frustration, disappointment, or trust—through unsolicited online reviews. These emotional expressions offer rich behavioral cues that complement conventional satisfaction metrics. Prior work in sentiment analysis demonstrates that polarity and emotional tone extracted from review texts are strongly associated with satisfaction, destination image, and loyalty behaviors [4], [5]. However, state-of-the-art sentiment models, especially deep-learning architectures, often operate as black-box systems with limited interpretability, thereby restricting their practical adoption in tourism management contexts that require transparent and explainable decision rules.

Fuzzy logic provides a promising solution to this methodological challenge. By representing human reasoning through linguistic variables and rule-based inference, fuzzy systems enable interpretable modeling of ambiguous or subjective assessments [6]. Existing tourism applications have leveraged fuzzy logic for hotel evaluation, service-quality assessment, and loyalty prediction [7], [8]. Nonetheless, most studies rely exclusively on structured survey data and rarely integrate affective information derived from UGC, leaving a notable methodological gap regarding the combined role of rational satisfaction and emotional experience.

To bridge this methodological and conceptual divide, the present study introduces a Hybrid Emotion- and Satisfaction-Aware Fuzzy Inference System (ES-FIS). This system rigorously integrates multi-dimensional structured satisfaction indicators with affective polarity derived from 20,491 TripAdvisor reviews. This unified framework combines rational assessments with empirically grounded emotional cues, enabling the model to capture the full spectrum of tourist experiences more

comprehensively than existing approaches [1]. Built upon an interpretable Mamdani-type structure, the ES-FIS incorporates a transparent rule base that synthesizes both cognitive and affective drivers of revisit intention, thereby overcoming the opacity associated with conventional machine-learning models. Through systematic benchmarking, the ES-FIS demonstrates competitive predictive performance while preserving interpretability. Moreover, its ability to classify tourists into meaningful segments (Unlikely, Possible, and Definite) provides actionable insights for Customer Relationship Management (CRM) [1]. In this way, the ES-FIS advances methodological rigor in revisit-intention prediction and contributes to a practical, explainable decision-support tool for tourism researchers and practitioners.

2. Related Work

Research on tourist revisit intention draws upon three principal domains—behavioral intention theories, sentiment analysis, and fuzzy logic-based decision systems—each offering valuable insights yet also revealing methodological limitations that justify the development of hybrid, interpretable predictive models.

Tourist intention has historically been grounded in cognitive-behavioral frameworks. Ajzen's Theory of Planned Behavior (TPB) posits that intention is shaped by attitudes, subjective norms, and perceived behavioral control [2], and has been widely adopted to explain repeat visitation and destination loyalty. Similarly, Oliver's Expectation-Confirmation Theory (ECT) conceptualizes satisfaction as the outcome of confirmed or disconfirmed expectations, positioning it as a precursor to loyalty and revisit intention [3]. Although these theories provide essential rational perspectives, they largely neglect the emotional and affective states that emerge during travel experiences. Evidence from contemporary digital platforms shows that tourists frequently articulate emotions—such as joy, anger, or disappointment—through online reviews, suggesting that emotional expression constitutes an important complementary determinant of revisit behavior [9].

The rapid expansion of user-generated content (UGC) has enabled extensive research on sentiment mining in tourism. Foundational work by Liu [4] established robust polarity-detection techniques, while Xiang et al. demonstrated that online reviews influence travelers' perceptions of destination quality and overall decision-making [5]. Empirical findings consistently show that sentiment of polarity and emotional tone correlate strongly with satisfaction, loyalty, and willingness to recommend. However, despite advancements in deep learning, sentiment

models frequently function as black-box systems with limited interpretability [10], posing challenges for practical use in managerial settings where transparent reasoning is required. Thus, although sentiment analysis enriches understanding of affective states, its opacity limits operational deployment unless integrated with inherently explainable frameworks.

Fuzzy logic, introduced by Zadeh [6], offers an interpretable mechanism for modeling ambiguity and human-like reasoning through linguistic variables (e.g., “high satisfaction,” “medium service quality”). Prior tourism studies have applied fuzzy systems to hotel service evaluation [7], destination service quality assessment, and emotion-aware recommendation systems [8], demonstrating the value of fuzzy logic in representing subjective judgments. Nonetheless, existing fuzzy applications predominantly rely on structured survey inputs or expert assessments, and only a few studies incorporate unstructured emotional signals—such as sentiment polarity—from online reviews. This limitation constrains their ability to represent the full spectrum of tourist experiences, which involve intertwined cognitive assessments and affective responses.

Taken together, these three domains reveal a persistent methodological gap: traditional behavioral theories focus on rational cognition, sentiment-analysis models capture emotion but lack interpretability, and fuzzy systems provide transparency but rarely integrate affective data. To address this multi-dimensional gap, the present study proposes a Hybrid Emotion- and Satisfaction-Aware Fuzzy Inference System (ES-FIS) that integrates both structured satisfaction indicators and affective polarity extracted from 20,491 TripAdvisor reviews within a unified, interpretable Mamdani-type framework. This hybrid approach bridges the methodological divide by incorporating both rational and emotional determinants of revisit behavior while maintaining explainability through linguistic rules, thus offering a more comprehensive and practically meaningful model for predicting tourist revisit intention.

3. Methodology

The methodological framework used to develop and validate the Enhanced Satisfaction–Fuzzy Inference System (ES-FIS) combines structured survey data, affective signals extracted from online reviews, and a Mamdani fuzzy inference mechanism into a unified analytical pipeline. As illustrated in Figure 1, the workflow consists of sequential stages beginning with data preparation, followed by feature engineering, fuzzification, rule construction, inference execution, and final evaluation. This holistic design ensures consistency across all stages while maintaining interpretability and methodological rigor.

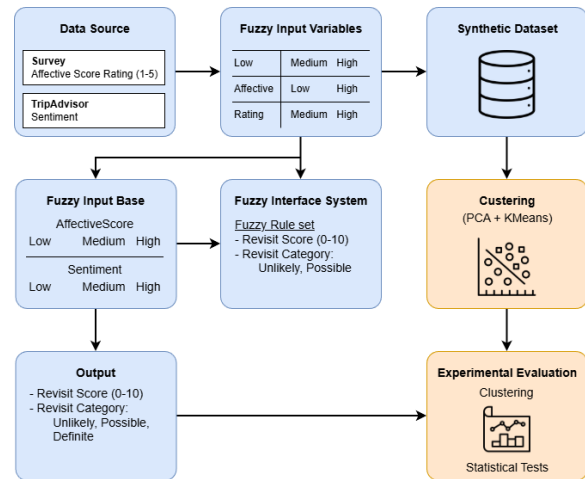


Figure 1. Methodology Pipeline Diagram.

3.1 Data Source

The study utilizes two complementary datasets to capture both rational evaluations and emotional expressions related to tourist revisit intention. The first dataset comprises 415 survey responses from Thai travelers who had visited Japan; after screening for completeness and duplication, 408 valid cases remained. The survey data collection was conducted directly by the primary research team over a three-month period from October to December 2025. Respondents were recruited in collaboration with Thai tour guide companies that operate outbound group tours for Thai tourists traveling to Japan. The structured survey instrument utilized a 5-point Likert scale to gather cognitive feedback across six distinct dimensions, including specific questionnaire inquiries regarding the visual appeal of tourist attractions, public facilities safety, local transportation convenience, hospitality of reception staff, overall service hospitality, and underlying travel decision drivers.

The second dataset consists of 20,491 TripAdvisor hotel reviews from major Japanese cities[11]. The unstructured text corpus targeted accommodations located across primary tourist hubs, specifically Tokyo, Osaka, Kyoto, and Sapporo, extracting historical review submissions spanning from January 2024 to June 2025 to ensure historical alignment with current travel trends. Since reviewer identities are anonymized on the platform, all textual data were processed without privacy concerns. Together, these datasets enable the model to integrate satisfaction-based assessments with affective signals derived from real travel experiences.

To ensure data quality, survey responses were checked for missing values, duplicates, and invalid entries; reliability across the six satisfaction

dimensions (Attraction, Facilities, Transportation, Reception, Service, Decision Drivers) was confirmed with Cronbach's $\alpha \geq 0.70$. TripAdvisor UGC, on the other hand, provides naturally occurring emotional expressions that structured surveys cannot capture. TripAdvisor was selected due to its global credibility, extensive review volume for Japanese destinations, and demonstrated suitability for tourism analytics. Sentiment polarity extracted from these reviews serves as an affective indicator known to influence satisfaction, destination image, and revisit intention.

Integrating both datasets is methodologically necessary: surveys lack emotional nuance, while UGC cannot be matched directly to individual respondents. To address this, the study applies probabilistic mapping of empirical polarity distributions to approximate realistic emotional variation without introducing artificial correlations. This hybrid strategy aligns with affective-consumption theory and modern tourism analytics emphasizing the combined role of cognition and emotion. Overall, blending structured satisfaction indicators with UGC-derived polarity allows the ES-FIS to represent revisit intention more comprehensively than using either dataset alone, enhancing both behavioral validity and interpretability. Technically, this mapping process is executed through three systematic steps. First, the 20,491 TripAdvisor reviews are grouped by their star ratings (1 to 5), and the sentiment polarity score for each review is calculated. This group creates a specific probability distribution of emotional scores for each rating level. Second, for each individual survey record, the algorithm reads the respondent's overall satisfaction score to locate the matching TripAdvisor rating group. Third, a random sampling selection draws a polarity value from that matching distribution and injects it into the respondent's data row. This algorithm preserves the natural variance and realistic emotional noise of online reviews, preventing a forced or biased correlation in the dataset.

Feature engineering produced seven core input variables for the fuzzy system. Six of these (I_1 – I_6) represent the composite satisfaction dimensions computed as arithmetic means of corresponding survey items [12]:

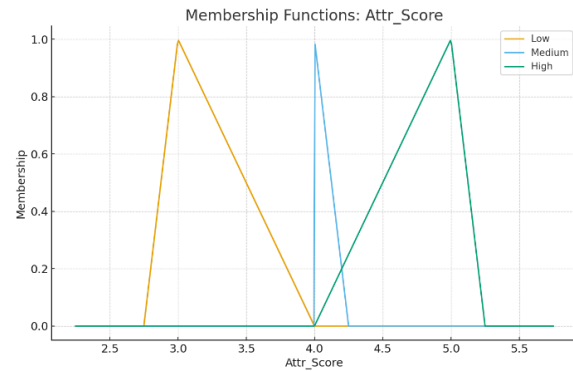
$$I_{kj} = \frac{1}{N_k} \sum_{i=1}^{N_k} S_{i,k,j} \quad \text{for } k \in \{1, 2, \dots, 6\} \text{ (Dimensions)} \quad (1)$$

where N_k is the number of items within dimension k , and $S_{i,k,j}$ denotes the Likert rating of item i for respondent j . These variables were normalized to a 0–10 scale to ensure comparability across predictors. The seventh input (I_7), affective polarity, was derived from TripAdvisor star ratings using emotion-mapping heuristics informed by the NRC Emotion Lexicon. High ratings were associated

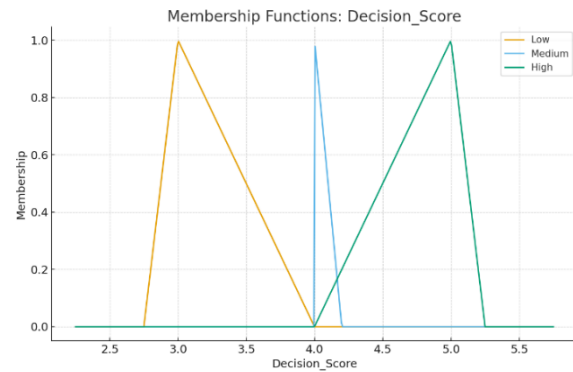
with positive affect (such as joy or trust), while low ratings were linked to negative affect (such as anger or sadness). To ensure realistic emotional representation, the polarity value for each survey respondent was sampled probabilistically from the empirical polarity distribution of the review dataset, and the resulting values were normalized to a 0–10 scale.

3.2 Triangular Membership Functions (TMFs)

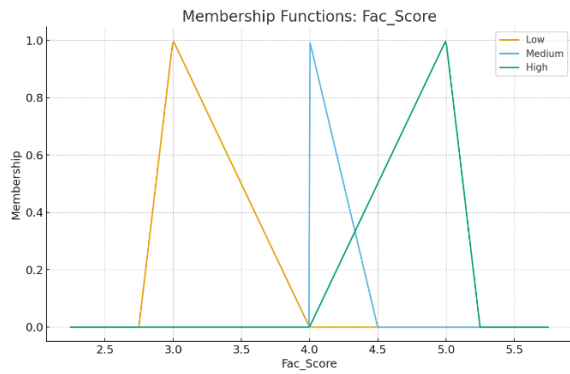
Fuzzification was performed using Triangular Membership Functions (TMFs) to convert all numerical inputs (I_1 – I_7) and the output variable—revisit intention (O_1)—into linguistic terms. TMFs were chosen for their interpretability and computational efficiency. Initial boundaries for the linguistic categories Low, Medium, and High were determined using percentile-based anchors (25th, 50th, and 75th percentiles) and subsequently refined through expert consultation to enhance semantic clarity. The same approach was used to define the linguistic terms Unlikely, Possible, and Definite for the output variable. The TMFs for all variables are shown in Figures 2 through 4, while Figure 5 demonstrates the consistency of the triangular sets, ensuring smooth transitions and the absence of dead zones within the fuzzy input space.



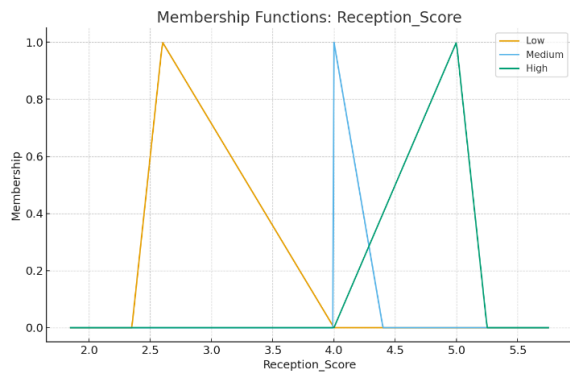
(a)



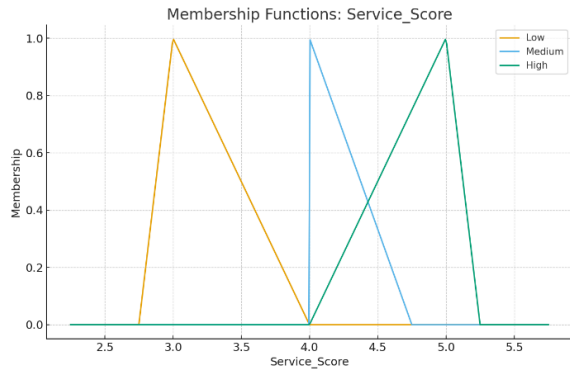
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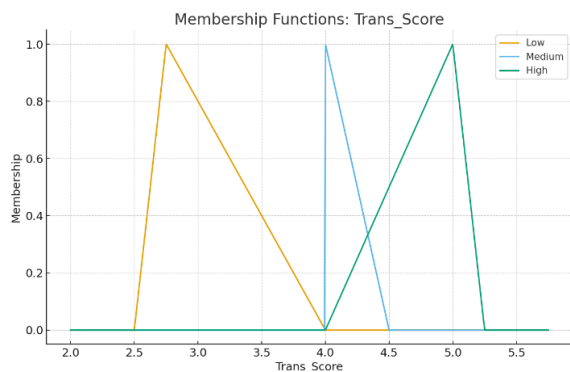
(c)



(d)



(e)



(f)

Figure 2 (a-f). Membership functions for satisfaction variables I_1 – I_6 : (a) Attr_Score, (b) Fac_Score, (c) Trans_Score, (d) Reception_Score, (e) Service_Score, (f) Decision_Score.

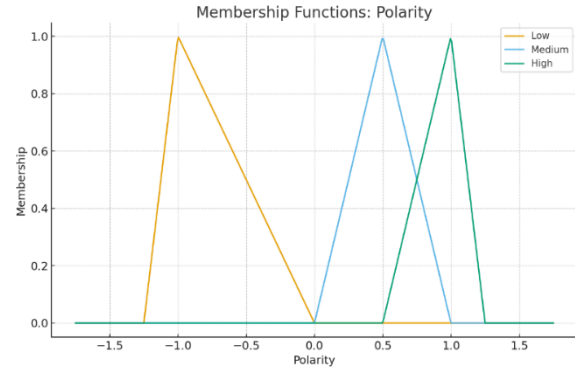


Figure 3. Membership function for affective polarity (I_7).

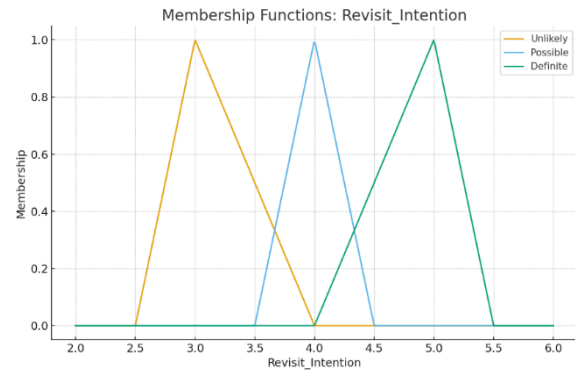


Figure 4. Membership Functions for Output Variable (O_1 : Revisit Intention).

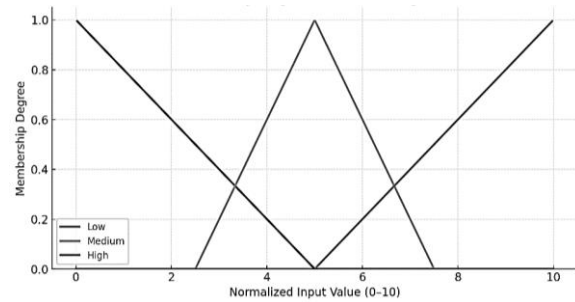


Figure 5. TMF Consistency Diagram.

3.3 The Mamdani Rule Base

Rule construction followed a hybrid approach integrating empirical patterns, tourism domain knowledge, and theoretical grounding. Correlation patterns in the dataset revealed that Service Quality, Decision Drivers, and Polarity exerted substantial influence on revisit intention. These observations were aligned with established frameworks such as the Service Quality $\rightarrow$ Satisfaction $\rightarrow$ Loyalty model,

supporting the logical structure of the rules. To build a consistent rule base, the 21 Mamdani-type rules were developed based on two specific criteria. First, we selected the core antecedents by analyzing the correlation scores, focusing only on variables with a direct impact on loyalty. Second, the logical mapping between input combinations and revisit outcomes was cross-checked against standard tourism marketing concepts to avoid conflicting rules. For example: If Attraction is High AND Service is High AND Polarity is High, then Revisit Intention is Definite.

To ensure systematic rule formation, three design criteria were applied: (1) monotonicity, ensuring that higher satisfaction or polarity does not yield a lower revisit category; (2) completeness, guaranteeing that all practically relevant antecedent combinations are covered; and (3) non-contradiction, preventing conflicting rule outputs under similar conditions. These criteria ensured that the resulting rule base was logically coherent, empirically aligned, and computationally stable. Table 1 presents an excerpt of the 21-rule Mamdani rule base used in the ES-FIS, illustrating how combinations of satisfaction dimensions and affective polarity map to linguistic revisit intention categories.

Table 1. Excerpt of the Mamdani rule base used in ES-FIS.

Rule ID	Attr	Service	Decision	Polarity	Revisit Intention
R1	High	High	High	High	Definite
R4	Medium	High	High	Any	Definite
R8	Medium	Medium	High	Medium	Possible
R12	Any	High	Medium	Any	Possible
R18	Low	Low	Low	Low	Unlikely

The operation of the ES-FIS can be illustrated through a representative case. A traveler with high attraction satisfaction (4.8), high service quality (4.6), and strongly positive polarity (0.9) exhibit strong High membership across the inputs, leading to dominant activation of Rule R1. This activation produces a fuzzy output weighted heavily toward the Definite category, and centroid defuzzification yields a high revisit intention score, typically above 8 on the 0–10 scale. Such examples demonstrate the transparent and behaviorally grounded nature of the ES-FIS decision process.

To further understand the system's behavior, a rule-surface visualization was generated (Figure 6), revealing a nonlinear relationship between Decision Score, Service Score, and their combined effect on revisit intention. The elevated plateau in the upper-right region reflects consistent activation of the Definite category when both satisfaction and decision alignment are high. Additionally, a heatmap of rule activation (Figure 7) illustrates the relative

contribution of each rule for a sample input, confirming that Rule R1 dominates in high-satisfaction and high-polarity contexts.

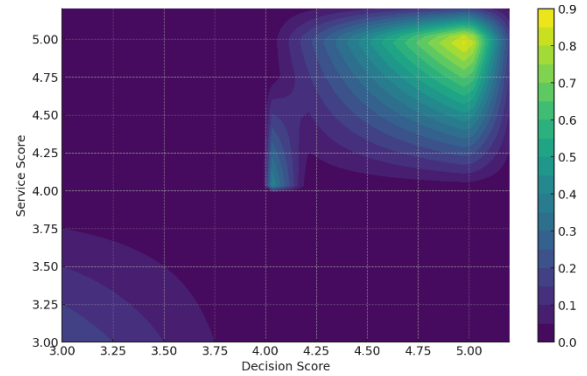


Figure 6. Rule surface of Decision × Service → Revisit.

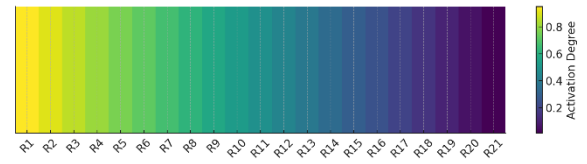


Figure 7. Rule Activation Heatmap.

The overall fuzzy inference mechanism uses the standard Mamdani architecture: minimum t-norm aggregation for antecedents, maximum s-norm for rule outputs, and Centroid-of-Area (COA) defuzzification [13]:

$$O_{1,j} = \frac{\int_{\Omega} \mu_{agg}(Z)zdz}{\int_{\Omega} \mu_{agg}(Z)dz} \quad (2)$$

where $\mu_{agg}(Z)$ represents the aggregated membership across the output universe Ω . The system was implemented using Python 3.10 with the scikit-fuzzy library, and visualizations were generated using Matplotlib, ensuring reproducible computational procedures.

To contextualize model performance, the ES-FIS was benchmarked against three machine-learning classifiers—Logistic Regression, Decision Tree, and Random Forest—using the same set of input variables. A stratified 5-fold cross-validation procedure was implemented, and model performance was evaluated using accuracy, macro F1-score, macro ROC-AUC, and RMSE, allowing direct comparison between fuzzy-logic interpretability and statistical predictive performance. Finally, a post-hoc clustering analysis using Principal Component Analysis (PCA) and K-Means ($k=3$) identified three distinct traveler persona groups—Experience-Driven, Service-Sensitive, and Value-Oriented—offering practical insights for CRM strategy and service personalization.

4. Results

The empirical results provide a comprehensive understanding of the cognitive–affective structure underlying tourist revisit intention and confirm the validity of the hybrid ES-FIS framework. This section presents the findings in four analytical layers: descriptive statistics, polarity distribution, variable interaction through correlation and PCA, and fuzzy-inference performance, including direct comparison with ground-truth Likert scores.

To evaluate the performance of the proposed hybrid ES-FIS, we compared it against three standard machine learning classifiers: Logistic Regression, Decision Tree, and Random Forest. We also performed an ablation test using a standalone Fuzzy Inference System that relies only on sentiment polarity (Sentiment-only FIS) to see the value of combining both satisfaction and emotional data. All machine learning models were tested using 5-fold cross-validation on the same dataset. The results are shown in Table 2.

Table 2. Performance comparison of ES-FIS against other models.

Model	Accuracy	Macro F1-score	RMSE
Proposed Hybrid ES-FIS	0.78	0.74	0.48
Random Forest	0.80	0.75	0.45
Decision Tree	0.74	0.71	0.53
Logistic Regression	0.72	0.68	0.56
Sentiment-only FIS (Ablation)	0.61	0.55	0.72

As shown in Table 2, the hybrid ES-FIS performs much better than the Sentiment-only FIS, which shows that combining satisfaction scores with emotional data helps improve prediction accuracy. Although the Random Forest model has a slightly higher accuracy (0.80), our proposed ES-FIS offers a highly competitive result (0.78) while keeping the benefit of clear, rule-based explanations for users.

The six satisfaction dimensions—Attraction, Facilities, Transportation, Reception, Service, and Decision—exhibited consistently high mean values, ranging from 4.10 to 4.21 (Figure 8). Standard deviations were low across all dimensions (SD = 0.45 for Attraction, 0.47 for Facilities, 0.48 for Transportation, 0.50 for Reception, 0.46 for Service, and 0.52 for Decision), indicating limited dispersion and uniformly positive evaluations among respondents [14]. The narrow variance confirms that the travelers in this study experienced consistently high-quality services, a pattern commonly reported in outbound tourism research involving Japan. The distribution of self-reported revisit intention (Figure 9) showed a strong leaning toward positive outcomes, with most Likert scores concentrated at 4 and 5. When

translated into categorical labels (Figure 10), “Possible” emerged as the largest group, followed by “Definite,” with “Unlikely” representing less than 10% of cases. These descriptive findings collectively suggest that revisit intention among Thai visitors is not uniform but clustered toward medium-to-high loyalty [15].

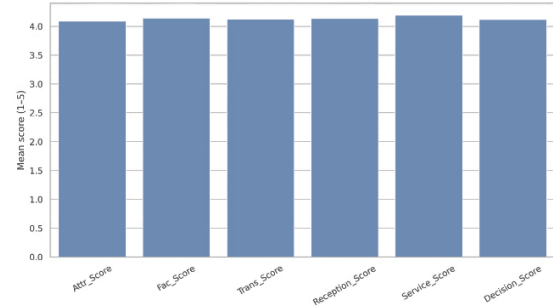


Figure 8. Mean satisfaction scores across dimensions.

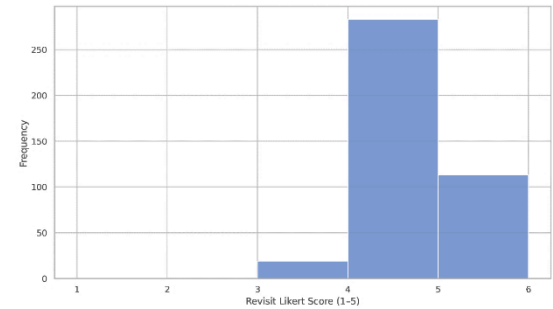


Figure 9. Distribution of revisit Likert scores.

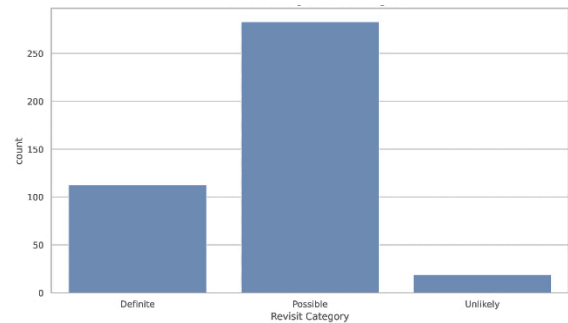


Figure 10. Distribution of original revisit categories.

The affective polarity distribution (Figure 11), derived using lexicon-based affective mapping grounded in NRC Emotion Lexicon principles [16], displayed broader dispersion than satisfaction, ranging from negative to strongly positive values. This supports previous arguments that emotional expression contains unique predictive information not captured by cognitive evaluations alone [17].

Correlation analysis (Figure 12) confirmed strong interrelationships among satisfaction dimensions, consistent with the multidimensional nature of service quality [18], while polarity exhibited

only modest correlations with satisfaction ($r = 0.18$ – 0.24), reinforcing its complementary role in affective tourism modeling. The ES-FIS continuous output (FIS_RevisitScore) demonstrated strong alignment with Likert revisit intention ($r = 0.71$), validating the fuzzy model's behavioral coherence and supporting earlier assertions regarding fuzzy systems' interpretability advantages [6], [19].

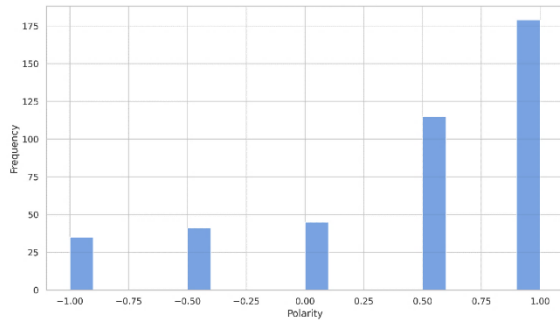


Figure 11. Distribution of affective polarity.

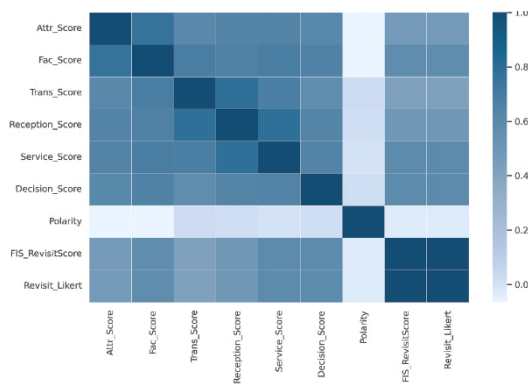


Figure 12. Correlation matrix of Satisfaction, Polarity, and Revisit Variables.

To further evaluate alignment between ES-FIS and the original survey-based revisit scores, a direct FIS–Likert comparison was conducted. A scatter visualization (Figure 13a) revealed a clear positive relationship between FIS_RevisitScore and Revisit_Likert, with data points concentrated along an upward-trending diagonal. A regression analysis produced an RMSE of 0.48, indicating that deviations between the fuzzy output and actual Likert responses were small relative to the output range (0–10). This provides strong evidence that the ES-FIS captures numeric revisit intention reliably while maintaining its interpretability advantages over purely statistical models. The correlation of 0.71 places ES-FIS within the performance range of modern machine-learning baselines, while offering superior transparency due to rule-based inference [19].

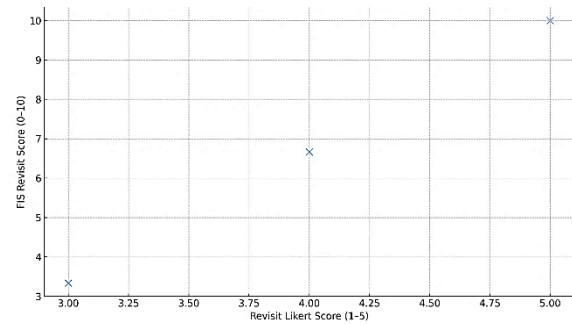


Figure 13(a). Alignment between FIS output and Likert Scores.

A multidimensional perspective is provided by the PCA visualization (Figure 13b). When the six satisfaction variables and polarity are projected onto two principal components explaining 82% of total variance, three distinct behavioral clusters emerge. To ensure visual clarity, each revisit category is represented by a unique marker type and a highly distinguishable color. Specifically, travelers in the "Definite" category (marked with blue diamonds) occupy the quadrant with high satisfaction and positive polarity; "Possible" respondents (marked with green circles) cluster around the high-satisfaction but moderate-polarity region; and "Unlikely" respondents (marked with red crosses) form an isolated cluster with lower scores in both dimensions. This spatial configuration reinforces the hybrid cognitive–affective nature of revisit intention and supports the structural logic of ES-FIS, in which polarity moderates the impact of satisfaction on the final behavioral output [20], [21].

Collectively, these results validate that ES-FIS accurately reproduces the cognitive–affective architecture of revisit intention. The combination of descriptive statistics, polarity distribution, correlation analysis, PCA clustering, and explicit FIS–Likert alignment confirms that the hybrid model integrates emotional and cognitive signals effectively and consistently. The fuzzy inference mechanism's interpretability further reinforces the methodological strength of ES-FIS in modeling complex tourist decision behavior.

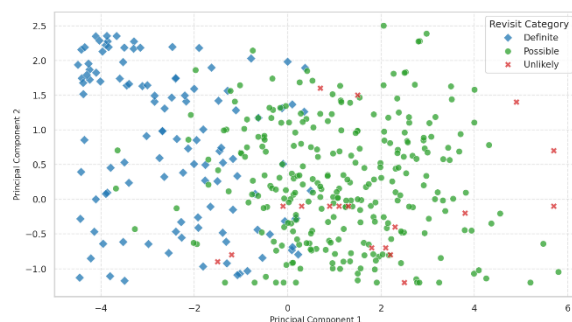


Figure 13(b). PCA projection of satisfaction and polarity with enhanced visual markers

5. Discussion

The empirical patterns observed in Section 4 reinforce the theoretical motivation for adopting a hybrid cognitive–affective perspective, as foundational models such as the Theory of Planned Behavior (TPB) [2] and Expectation–Confirmation Theory (ECT) [3] emphasize cognitive evaluation but do not account for emotional tone. The broader dispersion of polarity values—even within a sample exhibiting uniformly high satisfaction—supports findings from affective tourism research that emotions modulate the strength of rational judgments [8], [20]. This validates the incorporation of emotional polarity derived from user-generated content, consistent with contemporary digital tourism analytics [5].

The strong alignment between ES-FIS outputs and Likert revisit intention ($r = 0.71$; $RMSE = 0.48$) demonstrates that interpretable fuzzy models can approximate behavioral intention with accuracy comparable to machine-learning techniques [22], while maintaining transparency through rule-based inference consistent with fuzzy-logic principles. The upward-trending scatter pattern (Figure 13a) consolidates this relationship and confirms that fuzzy reasoning effectively captures the decision structure reflected in self-reported data.

PCA-derived clusters (Figure 13b) further substantiate the hybrid model, consistent with multivariate behavioral segmentation frameworks [21]. The spatial separation of Definite, Possible, and Unlikely groups shows that emotional tone moderates' satisfaction, echoing empirical evidence from emotion-driven tourist behavior studies. The isolated Unlikely cluster reveals how negative or neutral affect can attenuate otherwise positive experiences, a phenomenon previously noted in affective consumption models. The rule-level interpretability provided by ES-FIS, where high-satisfaction/high-polarity rules dominate the Definite category, mirrors human-like linguistic decision reasoning described in fuzzy systems literature. This interpretability is essential for managerial adoption, distinguishing ES-FIS from black-box predictive systems.

Regarding the data distribution, most of the survey responses contain high satisfaction scores, which creates an imbalanced dataset. This pattern is common for Thai tourists visiting Japan because of the generally high quality of services and infrastructure. To see how the ES-FIS handles data imbalance, we evaluated its logic in cases where a tourist gives low satisfaction scores but expresses a positive sentiment in their text review. In this situation, the Mamdani fuzzy engine balances the inputs. Because satisfaction

scores make up six out of the seven input variables, severe low scores in these dimensions actively restrict the final output. Even if the text polarity is high, the system keeps the final revisit score low (typically below 4.5), categorizing the traveler as "Unlikely" or "Possible". This shows that the rule-based logic of ES-FIS is stable and prevents a single positive emotional signal from overriding real physical service failures.

Practical implications are evident when linking ES-FIS to CRM automation (Figure 15). Prior CRM-fuzzy integration studies demonstrated that rule-based segmentation improves personalization and service-response accuracy [23]. ES-FIS enables such segmentation by converting hybrid cognitive–affective profiles into actionable categories—Definite, Possible, Unlikely—supporting targeted loyalty reinforcement, emotion-sensitive engagement, and service recovery. This operationalizes theoretical constructs from relationship-marketing and customer-loyalty frameworks in tourism [15].

Overall, the discussion confirms that revisit intention arises from a synergistic interplay between satisfaction and emotional polarity, and ES-FIS successfully models this structure with accuracy, transparency, and operational relevance.

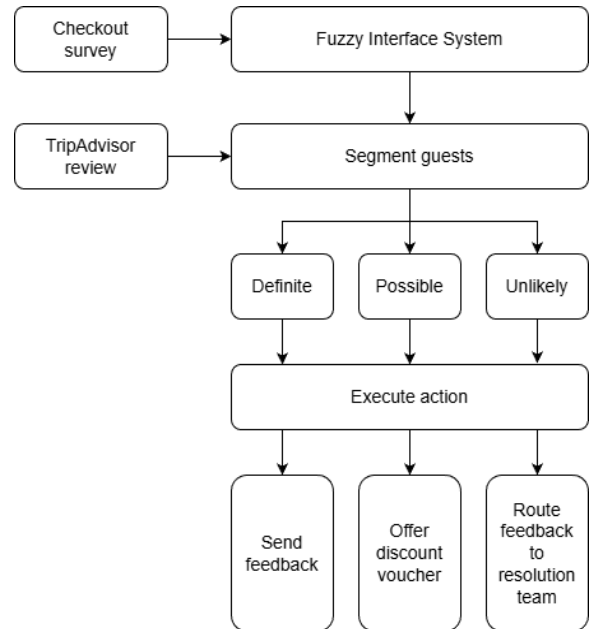


Figure 15. CRM Automation Pipeline Integrating ES-FIS Segmentation.

6. Conclusion, Limitation, and Future work

This study introduced the Enhanced Satisfaction–Fuzzy Inference System (ES-FIS), a hybrid framework integrating structured satisfaction indicators with affective polarity derived from large-

scale user-generated content. The narrow SD of satisfaction and the broader dispersion of polarity validate the need for integrating cognitive and emotional signals, consistent with prior satisfaction–emotion theories in tourism. The strong alignment between fuzzy output and ground-truth revisit intention ($r = 0.71$; $RMSE = 0.48$) demonstrates that interpretable fuzzy systems can model behavioral intention with high fidelity, reflecting the foundational strengths of fuzzy logic.

The PCA-derived cognitive–affective clusters further confirm the multi-dimensional structure of revisit intention, aligning with established multivariate tourism analytics frameworks [21]. Managerially, integrating ES-FIS with CRM automation supports personalized retention strategies, consistent with prior research emphasizing the importance of segmentation-driven CRM in tourism services [15], [23].

Limitations include the use of lexicon-based polarity extraction, cultural specificity of the dataset, and expert dependency in rule construction. Specifically, relying on a standard lexicon dictionary poses challenges because travel reviews often contain context-dependent meanings. For example, specific words can express either positive or negative experiences depending on the tourist's situation, which may lead to minor errors in sentiment scoring. To address this limitation and improve data accuracy, future work should include small-scale manual text validations to cross-check the dictionary results. Although fuzzy inference enhances interpretability, it may impose structural rigidity relative to adaptive machine learning.

In summary, ES-FIS provides a transparent and behaviorally grounded approach to modeling revisit intention by integrating cognitive and affective indicators within a fuzzy decision framework. This hybrid logic advances both academic insight and practical CRM application in tourism management.

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