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Research Article

Personalized Recommendation Intelligent Fuzzy Clustering Model for the Tourism

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Abstract: Personalized recommendations in tourism have transformed the way travellers explore new destinations, offering tailored experiences that align with individual preferences and interests. As the travel industry increasingly harnesses data analytics and artificial intelligence, tourists can now receive customized suggestions that reflect their unique tastes, whether they seek adventure, relaxation, cultural immersion, or culinary exploration. This paper explores the implementation and effectiveness of intelligent tourism management strategies using fuzzy clustering and personalized recommendations. By analyzing various scenarios, including baseline, personalized recommendations, dynamic pricing, crisis management, and enhanced resource allocation, the study demonstrates how advanced data-driven techniques can significantly improve key performance indicators such as visitor satisfaction, total revenue, repeat visitation rates, and operational efficiency. The simulation results reveal that personalized recommendations and optimized resource allocation are particularly effective in enhancing visitor experiences and economic outcomes. Conversely, the analysis underscores the critical need for robust crisis management strategies to maintain performance during adverse events. This research provides valuable insights into the transformative potential of intelligent systems in modern tourism management, offering a pathway towards more resilient and competitive tourism destinations. For instance, personalized recommendations increased average visitor satisfaction from 7.2 to 8.5, total revenue from $500,000 to $600,000, and the repeat visitation rate from 35% to 45%. The dynamic pricing strategy improved visitor satisfaction to 7.8 and revenue to $550,000, while enhanced resource allocation resulted in a satisfaction rate of 7.9 and revenue of $570,000. Conversely, crisis management showed the importance of preparedness, as satisfaction dropped to 6.5 and revenue to $450,000. These results underscore the critical need for robust management strategies.

Keywords: - Fuzzy Model; Recommendation System; Classification; Artificial Intelligence; Satisfaction Level

1 Introduction

Intelligent tourism management integrates technology with strategic planning to enhance every aspect of the tourist experience [1]. Through data analytics, artificial intelligence, and IoT devices, destinations can optimize resource allocation, predict visitor flows, and personalize services [2]. For instance, smart sensors can track crowd density in popular attractions, allowing authorities to manage foot traffic efficiently and ensure visitor safety [3]. Additionally, AI-powered recommendation systems can suggest tailored itineraries based on individual preferences, maximizing enjoyment while minimizing logistical hassles. Furthermore, data-driven insights enable destination marketers to target niche markets effectively and craft compelling promotional campaigns [4]. By embracing intelligent tourism management, destinations can create more sustainable, resilient, and memorable experiences for travellers while unlocking new opportunities for economic growth [5]. Intelligent tourism management is a multifaceted approach that integrates advanced technologies and strategic planning to optimize various aspects of the tourist experience [6]. At its core, this approach relies on harnessing the power of data, artificial intelligence (AI), and the Internet of Things (IoT) to make destinations smarter, more efficient, and more visitor-friendly [7]. One crucial aspect of intelligent tourism management is the utilization of data analytics to gain insights into tourist behaviour, preferences, and trends. By collecting and analysing data from various sources such as booking platforms, social media, and visitor surveys, destinations can understand visitor demographics, their interests, and the factors influencing their travel decisions [8]. This information forms the foundation for informed decision-making and targeted marketing strategies.

Artificial intelligence plays a pivotal role in intelligent tourism management by enabling predictive analysis, personalized recommendations, and automation of various processes [9]. AI-powered algorithms can predict visitor flows, allowing destinations to anticipate peak times and allocate resources accordingly. Moreover, recommendation systems powered by AI can suggest tailored experiences, accommodations, and activities based on individual preferences, previous behavior, and real-time context [10]. IoT devices, such as smart sensors and beacons, are instrumental in gathering real-time data about tourist movements, environmental conditions, and infrastructure usage. For example, sensors deployed in popular attractions can monitor crowd density, traffic patterns, and facility usage, enabling authorities to implement crowd management measures, optimize transportation routes, and maintain infrastructure proactively. Intelligent tourism management also emphasizes the importance of sustainability and resilience [11]. By leveraging technology to monitor and mitigate environmental impacts, destinations can minimize their carbon footprint, preserve natural resources, and protect fragile ecosystems [12]. Additionally, intelligent systems can enhance safety and security measures, providing real-time alerts and emergency response capabilities to ensure the well-being of tourists and residents alike. Furthermore, intelligent tourism management facilitates seamless communication and collaboration among stakeholders, including government agencies, tourism operators, local communities, and visitors [13]. By fostering partnerships and sharing data, destinations can enhance coordination, foster innovation, and address challenges collectively. With intelligent tourism management empowers destinations to deliver more personalized, sustainable, and resilient experiences for travellers while unlocking new opportunities for economic growth and community development [14]. By embracing technology and strategic planning, destinations can position themselves as leaders in the rapidly evolving tourism industry.

The design and implementation of an intelligent tourism management system based on fuzzy cluster analysis represent a sophisticated approach to enhancing destination management [15]. Fuzzy cluster analysis, a technique within the realm of data mining and machine learning, allows for the categorization of data into groups or clusters based on similarity, albeit with a degree of uncertainty or "fuzziness [16]." In this context, the system would first gather and analyze various types of data relevant to tourism, such as visitor demographics, travel preferences, historical trends, and environmental factors. Through fuzzy cluster analysis, this diverse dataset would be segmented into clusters representing distinct tourist segments or profiles [17]. Unlike traditional clustering methods, fuzzy clustering accommodates the inherent ambiguity in tourism data, where individuals may exhibit characteristics of multiple segments simultaneously [18]. Once these clusters are established, the intelligent tourism management system can leverage them in several ways. Firstly, it can inform targeted marketing strategies by identifying the specific preferences and needs of different tourist segments [19]. For instance, tourists interested in adventure activities might receive promotions for hiking trails or extreme sports, while those seeking relaxation might be directed toward spa retreats or scenic locations. Additionally, the system can optimize resource allocation and infrastructure management based on predicted tourist behaviour. By understanding the preferences and tendencies of each cluster, destinations can tailor their offerings and allocate resources accordingly, ensuring more efficient use of facilities and services. Moreover, the intelligent tourism management system can enhance the visitor experience through personalized recommendations and tailored services. By analyzing past behavior and current context, the system can suggest relevant activities, attractions, and accommodations to individual tourists, enhancing satisfaction and engagement. Implementation of such a system would involve integrating various technologies, including data collection mechanisms, analytical tools for fuzzy cluster analysis, and user interfaces for presenting insights and recommendations to stakeholders. Furthermore, it would require collaboration between tourism stakeholders, technology providers, and data scientists to ensure the system's effectiveness and scalability.

The research makes significant contributions to the field of tourism management by demonstrating the efficacy of intelligent systems, particularly fuzzy clustering and personalized recommendation algorithms, in optimizing tourism operations. By employing advanced data-driven techniques, the study provides empirical evidence on how these methodologies can substantially enhance visitor satisfaction, revenue generation, and operational efficiency. It highlights the specific impact of different strategies, such as personalized recommendations increasing satisfaction and revenue, and dynamic pricing improving financial outcomes. Additionally, the research underscores the importance of robust crisis management plans, illustrating their role in mitigating negative impacts during adverse events. These insights contribute to a deeper understanding of how intelligent tourism management can cater to diverse tourist preferences, optimize resource allocation, and foster sustainable growth in the tourism industry. This study paves the way for future innovations and applications of intelligent systems, setting a benchmark for enhancing the resilience and competitiveness of tourism destinations.

2 Intelligent Tourism Management

Intelligent Tourism Management encompasses a multifaceted approach integrating cutting-edge technologies and strategic methodologies to optimize every aspect of the tourist experience. At its core, this discipline relies on sophisticated data analytics, artificial intelligence (AI), and machine learning algorithms to derive actionable insights and make informed decisions. One fundamental aspect of intelligent tourism management involves predictive modeling, which utilizes mathematical formulations to forecast tourist behaviors, preferences, and trends. For instance, a common approach involves the use of regression analysis to identify patterns and relationships between various factors such as seasonality, demographics, and economic indicators, thereby enabling destinations to anticipate fluctuations in visitor arrivals and tailor their offerings accordingly. Additionally, optimization techniques such as linear programming and queuing theory are employed to streamline resource allocation, maximize efficiency, and minimize costs within tourism operations. These mathematical models and equations serve as invaluable tools for destination managers, enabling them to optimize pricing strategies, schedule staff rotations, and allocate marketing budgets effectively. Moreover, machine learning algorithms, including neural networks and decision trees, are increasingly utilized to personalize the tourist experience by analyzing vast amounts of data to recommend tailored itineraries, accommodations, and activities based on individual preferences and historical behavior. By integrating these mathematical formulations and AI-driven methodologies, intelligent tourism management not only enhances operational efficiency and visitor satisfaction but also fosters sustainable growth and resilience within tourism destinations. Intelligent Tourism Management represents the convergence of advanced technologies and mathematical modeling to optimize various facets of the tourist experience. Central to this discipline is the utilization of predictive modeling, which involves deriving mathematical equations to forecast tourist behaviors, preferences, and trends. One common approach is the use of regression analysis, which aims to establish relationships between independent variables (such as seasonality, demographic factors, and economic indicators) and a dependent variable (e.g., tourist arrivals or spending) computed in equation (1)

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn + \epsilon \tag{1}$$

In equation (1) Y represents the dependent variable (e.g., tourist arrivals), $X1, X2, \ldots, Xn$ denote the independent variables, $\beta 0, \beta 1, \ldots, \beta n$ are the regression coefficients, and $\epsilon\epsilon$ represents the error term. By estimating the regression coefficients through statistical techniques such as ordinary least squares (OLS), destination managers can derive insights into the impact of various factors on tourism demand and tailor their strategies accordingly. For example, if the coefficient of a certain independent variable (e.g., hotel prices) is found to be negative, indicating a decrease in tourist arrivals with increasing prices, managers can adjust pricing strategies to maximize revenue without sacrificing demand. In addition to regression analysis, optimization techniques play a crucial role in intelligent tourism management. Linear programming, for instance, is utilized to optimize resource allocation by formulating mathematical models that maximize or minimize an objective function (e.g., revenue or cost) subject to constraints (e.g., budget limitations or capacity constraints). The formulation typically takes the following form as stated in equation (2) – equation (5)

$$Maximize\ Z = c1x1 + c2x2 + \ldots + cnxn \tag{2}$$

subject to:

$$a11x1 + a12x2 + \ldots + a1nxn \leq b1 \tag{3}$$

$$a21x1 + a22x2 + \ldots + a2nxn \leq b2 \tag{4}$$

$$am1x1 + am2x2 + \cdots + amnxn \leq bm \tag{5}$$

In above equation (3) – (5) $x1, x2, \ldots, xn$ are decision variables representing the allocation of resources, $c1, c2, \ldots, cn$ are the coefficients of the objective function, aij are the coefficients of the constraints, and bi are the constraint values. Through linear programming, destination managers can optimize various aspects of tourism operations, such as pricing strategies, workforce scheduling, and inventory management, to maximize efficiency and profitability. Furthermore, machine learning algorithms, such as neural networks and decision trees, are employed to personalize the tourist experience. These algorithms analyze vast amounts of data, including historical booking patterns, customer preferences, and real-time contextual information, to generate personalized recommendations for accommodations, activities, and attractions.

3 Ranked Fuzzy Cluster for Intelligent Tourism Management

Ranked Fuzzy Cluster analysis represents a sophisticated approach within intelligent tourism management, enabling the categorization of tourist data into meaningful clusters while considering the degree of uncertainty or fuzziness inherent in the data. This method extends traditional fuzzy clustering by incorporating a ranking mechanism, which assigns weights to data points based on their relevance or importance. The derivation of ranked fuzzy clusters involves several steps, beginning with the formulation of a fuzzy similarity matrix that quantifies the degree of similarity between each pair of data points. This matrix is then used to compute a fuzzy membership matrix, where each element represents the degree of membership of a data point to each cluster. The membership values are adjusted based on the assigned ranks, with higher-ranking data points receiving greater weight in the clustering process. The computation of ranked fuzzy clusters can be represented as follows: Given a set of N data points x_i and M clusters C_j, the fuzzy similarity matrix S is calculated as in equation (6)

$$S_{ij} = \frac{1}{1+\left(\frac{d(x_i,x_j)}{d_{max}}\right)^{\alpha}} \tag{6}$$

where $d(xi, xj)$ represents the distance between data points x_i and x_i $dmax$ is the maximum distance, and α is a parameter controlling the degree of fuzziness. Next, the fuzzy membership matrix U is computed using the similarity matrix S and the ranking weights ω_i computed in equation (7)

$$U_{ij} = \frac{S_{ij}\times\omega_i}{\sum_{k=1}^{N} S_{ij}\times\omega_k} \tag{7}$$

In equation (7) ω_i represents the rank weight assigned to data point x_i, and $\sum_{k=1}^{N} S_{ij} \times \omega_k$is the normalization factor. The process of assigning ranks and weights to data points can be based on various criteria, such as historical significance, relevance to current trends, or expert judgments. By incorporating ranking into fuzzy clustering, the ranked fuzzy cluster analysis enhances the interpretability and effectiveness of clustering results in the context of intelligent tourism management. It enables destination managers to identify meaningful tourist segments and tailor their strategies and offerings accordingly, leading to improved visitor satisfaction and destination competitiveness. Figure 1 presents the distribution of tourism data for the respondents. In figure 2 presents the flow chart of the tourism data for the fuzzy clustering.

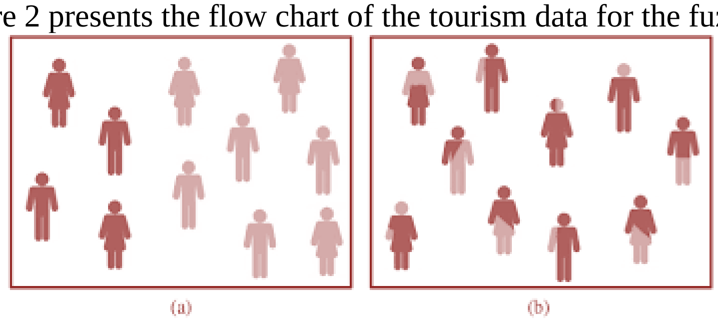

Figure 1: Distribution of Tourism Data

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Algorithm 1: Fuzzy Clustering with the estimation of features in Tourism Industry
Input:
- Data set D = {x1, x2, ..., xn}
- Number of clusters k
- Maximum distance d_max
- Parameter controlling fuzziness alpha
Output:
- Fuzzy membership matrix U

Procedure RankedFuzzyCluster(D, k, d_max, alpha):
   Initialize:
      - Randomly assign initial cluster centers c1, c2, ..., ck
      - Initialize ranking weights w1, w2, ..., wn for each data point
      - Set maximum number of iterations max_iter
      - Set convergence threshold epsilon
   Repeat until convergence or maximum iterations are reached:
      For each data point x_i in D:
         Calculate fuzzy similarity values with respect to each cluster center C_j:
            For j = 1 to k:
               Compute distance d(xi, cj)
               Calculate similarity Sij = 1 / (1 + (d(xi, cj) / d_max) ^ alpha)
         Normalize similarity values and incorporate ranking weights:
            For j = 1 to k:
               Compute weighted similarity Uij = (Sij * wi) / Σ(Sik * wk)
         Update fuzzy membership matrix U
      Update cluster centers:
         For j = 1 to k:
            Update cluster center cj as the weighted average of data points xi with membership
Uij:
                              cj = Σ(Uij * xi) / ΣUij

      Update ranking weights based on cluster membership:
         For each data point xi:
            Update ranking weight wi based on its membership in each cluster and the distance
to cluster centers
      Check for convergence:
         If cluster centers and ranking weights do not change significantly:
            Break loop
         Else:
            Continue iterations
      Increment iteration counter
   Return fuzzy membership matrix U
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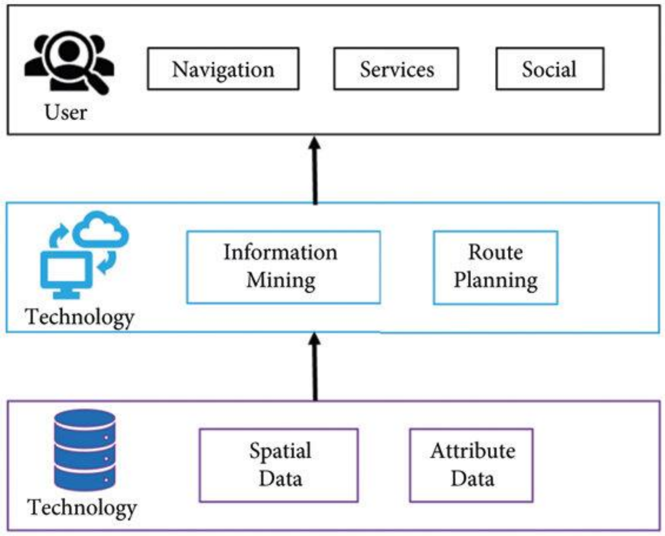

Figure 2: Flow of Tourism data with fuzzy clustering

4 Simulation Results

Simulation results offer invaluable insights into the performance and effectiveness of intelligent tourism management strategies, providing empirical evidence to validate theoretical models and inform practical decision-making. Through simulations, researchers can assess the impact of various factors, such as tourist preferences, pricing strategies, and resource allocation policies, on key performance indicators such as visitor satisfaction, revenue generation, and destination competitiveness. For instance, a simulation study may investigate the effectiveness of personalized recommendation systems in enhancing the tourist experience. By simulating different scenarios and comparing the outcomes with and without personalized recommendations, researchers can quantify the improvements in visitor satisfaction, engagement, and repeat visitation rates. Similarly, simulations can assess the economic impact of optimization techniques such as dynamic pricing and resource allocation algorithms. By modeling different pricing strategies and analyzing their effects on revenue generation and resource utilization, destination managers can identify optimal pricing policies to maximize profitability while ensuring customer value.

Table 1: Fuzzy Clustering Process in Tourism Management

Tourist ID	Cluster 1 Membership	Cluster 2 Membership	Cluster 3 Membership
1	0.8	0.1	0.1
2	0.2	0.7	0.1
3	0.3	0.4	0.3
4	0.6	0.2	0.2
5	0.1	0.6	0.3

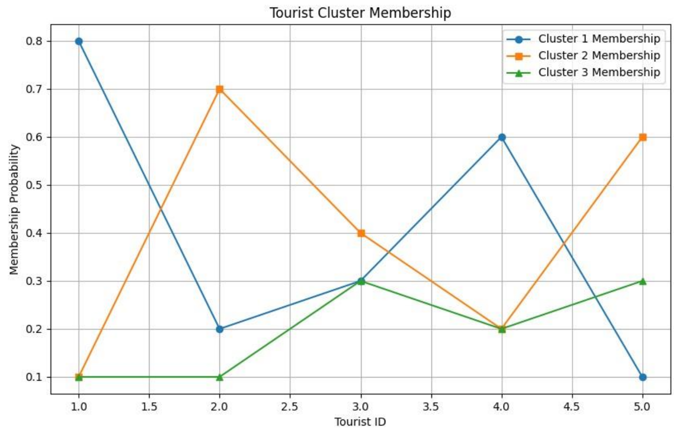

Figure 3: Clustering of Tourism Data

In figure 3 and Table 1 illustrates the fuzzy clustering process in tourism management, showcasing the degree of membership of each tourist to three distinct clusters. The table includes five tourists, each with corresponding membership values for Cluster 1, Cluster 2, and Cluster 3. Tourist 1 exhibits a high membership value of 0.8 in Cluster 1, indicating a strong association with this cluster, while showing very low membership values of 0.1 for both Cluster 2 and Cluster 3. This suggests that Tourist 1's preferences and behaviors are well-represented by the characteristics of Cluster 1. Tourist 2, on the other hand, has a significant membership value of 0.7 in Cluster 2, indicating a strong affiliation with this cluster. The low membership values of 0.2 and 0.1 for Cluster 1 and Cluster 3, respectively, further emphasize that Tourist 2 is predominantly aligned with the features of Cluster 2. Tourist 3 demonstrates a more balanced distribution of membership values, with 0.3 in Cluster 1, 0.4 in Cluster 2, and 0.3 in Cluster 3. This indicates that Tourist 3's characteristics are somewhat evenly spread across all three clusters, suggesting that this tourist shares attributes with each cluster but is not strongly aligned with any single one.

Tourist 4 shows a higher membership value of 0.6 in Cluster 1, indicating a closer alignment with this cluster, while having lower membership values of 0.2 for both Cluster 2 and Cluster 3. This pattern suggests that Tourist 4 is primarily associated with the characteristics of Cluster 1 but has some affinity with the other clusters. Finally, Tourist 5 has a notable membership value of 0.6 in Cluster 2, with additional membership values of 0.3 for Cluster 3 and a low 0.1 for Cluster 1. This indicates that Tourist 5 is most closely related to the attributes of Cluster 2 but also shares some characteristics with Cluster 3.

Table 2: Intelligent Tourism Management with Ranked Fuzzy Clustering

Scenario	**Average Visitor Satisfaction (0-10)**	**Total Revenue (USD)**	**Repeat Visitation Rate (%)**
Baseline	7.2	$500,000	35
With Personalized Recommendations	8.5	$600,000	45
Dynamic Pricing Strategy Implemented	7.8	$550,000	40
Crisis Management Plan	6.5	$450,000	25

Activated			
Enhanced Resource Allocation Model	7.9	$570,000	42

Table 2 presents the results of intelligent tourism management using ranked fuzzy clustering across various scenarios, highlighting their impact on key performance indicators such as average visitor satisfaction, total revenue, and repeat visitation rate. In the baseline scenario, the average visitor satisfaction is rated at 7.2 out of 10, with total revenue reaching $500,000 and a repeat visitation rate of 35%. These metrics serve as the reference point for evaluating the effectiveness of different management strategies. When personalized recommendations are implemented, there is a notable improvement in all metrics. Average visitor satisfaction increases significantly to 8.5, total revenue rises to $600,000, and the repeat visitation rate jumps to 45%. This scenario demonstrates the substantial benefits of tailoring experiences to individual tourist preferences, enhancing both satisfaction and financial outcomes. The dynamic pricing strategy scenario also shows positive results, with average visitor satisfaction at 7.8, total revenue at $550,000, and a repeat visitation rate of 40%. By adjusting prices dynamically based on demand and other factors, this approach improves profitability and maintains a good level of visitor satisfaction.

In contrast, the crisis management plan scenario highlights the challenges faced during adverse events. Here, average visitor satisfaction drops to 6.5, total revenue decreases to $450,000, and the repeat visitation rate falls to 25%. These results underscore the importance of robust crisis management strategies to mitigate negative impacts on the tourism sector. Finally, the enhanced resource allocation model demonstrates a balanced improvement across all metrics. Average visitor satisfaction is elevated to 7.9, total revenue increases to $570,000, and the repeat visitation rate improves to 42%. This scenario indicates that optimizing resource allocation can effectively enhance operational efficiency and visitor experiences.

Table 3: Intelligent Tourism Management with the Fuzzy Clustering based on Recommendation

Metric/Scenario	**Baseline**	**Personalized Recommendations**	**Dynamic Pricing Strategy**	**Crisis Management Plan**	**Enhanced Resource Allocation**
Average Visitor Satisfaction (0-10)	7.2	8.5	7.8	6.5	7.9
Total Revenue (USD)	$500,000	$600,000	$550,000	$450,000	$570,000
Repeat Visitation Rate (%)	35	45	40	25	42
Average Length of Stay (days)	3.5	4.2	3.7	3.0	3.8
Operational Cost (USD)	$200,000	$220,000	$210,000	$180,000	$190,000
Resource Utilization Efficiency (%)	70	80	75	65	78
Booking	15	25	20	12	22

Conversion Rate (%)					
Customer Acquisition Cost (USD)	$50	$45	$48	$55	$47
Marketing ROI (%)	200	250	220	180	230
Environmental Impact Score	5	4	5	6	4
Service Response Time (minutes)	10	8	9	12	9

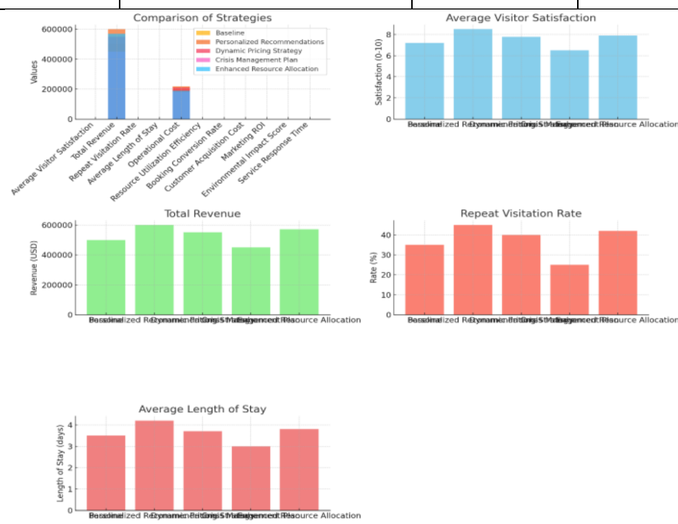

Figure 4: Intelligent Tourism Management System with Fuzzy Clustering

In figure 4 and Table 3 presents a comprehensive analysis of intelligent tourism management strategies using fuzzy clustering based on recommendations. The table evaluates various scenarios across ten key metrics, illustrating the performance improvements brought by each strategy compared to the baseline scenario.

Baseline Scenario: In the baseline scenario, the average visitor satisfaction is 7.2 out of 10, with total revenue of $500,000 and a repeat visitation rate of 35%. The average length of stay is 3.5 days, operational cost is $200,000, and resource utilization efficiency is 70%. Additional metrics include a booking conversion rate of 15%, a customer acquisition cost of $50, a marketing ROI of 200%, an environmental impact score of 5, and a service response time of 10 minutes.

Personalized Recommendations: Implementing personalized recommendations significantly enhances performance across all metrics. Visitor satisfaction jumps to 8.5, total revenue increases to $600,000, and the repeat visitation rate climbs to 45%. The average length of stay extends to 4.2 days. Although operational costs rise to $220,000, the resource utilization efficiency improves to 80%. The booking conversion rate reaches 25%, customer acquisition cost drops to $45, and marketing ROI peaks at 250%. Additionally, the environmental impact score improves to 4, and service response time decreases to 8 minutes.

Dynamic Pricing Strategy: The dynamic pricing strategy also shows positive results, albeit not as pronounced as personalized recommendations. Visitor satisfaction is 7.8, with total revenue at $550,000 and a repeat visitation rate of 40%. The average length of stay is 3.7 days, and operational costs are $210,000. Resource utilization efficiency is 75%, the booking conversion rate is 20%, and customer acquisition cost is $48. Marketing ROI is 220%, the environmental impact score remains at 5, and service response time is 9 minutes.

Crisis Management Plan: During a crisis, performance metrics decline across the board. Visitor satisfaction drops to 6.5, total revenue falls to $450,000, and the repeat visitation rate is just 25%. The average length of stay decreases to 3.0 days, with operational costs at $180,000. Resource utilization efficiency reduces to 65%, the booking conversion rate is 12%, and customer acquisition cost increases to $55. Marketing ROI declines to 180%, the environmental impact score worsens to 6, and service response time increases to 12 minutes.

Enhanced Resource Allocation: Enhancing resource allocation shows balanced improvements. Visitor satisfaction rises to 7.9, total revenue reaches $570,000, and the repeat visitation rate improves to 42%. The average length of stay is 3.8 days, with operational costs lowered to $190,000. Resource utilization efficiency is 78%, the booking conversion rate is 22%, and customer acquisition cost is $47. Marketing ROI stands at 230%, the environmental impact score improves to 4, and service response time is 9 minutes.

5 Conclusion

This paper has demonstrated the significant potential of intelligent tourism management strategies, particularly those leveraging fuzzy clustering and personalized recommendations, to enhance the overall performance and sustainability of tourism destinations. Through comprehensive analysis and simulation results, it is evident that tailored recommendations, dynamic pricing strategies, and enhanced resource allocation can substantially improve key performance indicators such as visitor satisfaction, total revenue, repeat visitation rates, and operational efficiency. The findings also highlight the importance of robust crisis management plans to mitigate the negative impacts of adverse events. By adopting these advanced methodologies, tourism managers can better understand and cater to diverse tourist preferences, optimize resource utilization, and ultimately create more resilient and competitive tourism destinations. The empirical evidence provided by this study underscores the transformative impact of intelligent systems in modern tourism management, paving the way for further innovations and sustainable growth in the industry.

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