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ENHANCING TOURIST EXPERIENCE: A FUZZY TOPSIS APPROACH TO DESTINATION RECOMMENDATION SYSTEMS

Nutchanat BUASRI
Mahasarakham University, Department of Informatics, Faculty of Geoinformatics, Maha Sarakham, Thailand, e-mail: nutchanat.b@msu.ac.th

Satith SANGPRADID*
Mahasarakham University, Department of Informatics, Faculty of Geoinformatics, Maha Sarakham, Thailand, e-mail: satith.s@msu.ac.th

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Abstract: To promote tourism effectively, it is essential to drive flexibility and sustainable growth within the sector. This requires a multi-faceted approach involving various organizations, as well as the development of systems that assist tourists in decision-making. The objective of this research is twofold: (1) to develop a recommendation system based on Fuzzy TOPSIS that integrates data from expert opinions, tourist behavior, and survey feedback, and (2) to design a system that enables tourists to make personalized destination choices through a recommendation process that accommodates diverse user preferences. This research employs a Multi-Criteria Decision Analysis (MCDA) approach using Fuzzy TOPSIS, leveraging survey data collected from 250 respondents, including tourism experts and visitors in Maha Sarakham province. The survey evaluated ten key criteria influencing destination selection, such as accessibility, safety services, and the availability of cafés and coffee shops. Accessibility and safety services emerged as the most critical factors, both receiving the highest scores of 9, while dining options also scored highly with a rating of 7. Conversely, criteria such as shuttle services and proximity to police stations were deemed less significant. According to the Fuzzy TOPSIS analysis ranked Phra That Na Dun, Wat Puttha Wanaram, and the Phra Yuen Mongkhon Buddha Image as the top three attractions, showcasing their strong alignment with tourist preferences. Lower-ranked sites, such as Ban Chiang Hian Museum and Chi Long Forest Park, highlight opportunities for development through infrastructural improvements and enhanced marketing efforts. The system's user satisfaction evaluation demonstrated favorable results, with high ratings for decision-making capability (4.67) and ease of use (4.67), reflecting the system's ability to align recommendations with user preferences effectively. Quantitative evaluations of the system yielded a precision of 85%, recall of 80%, and an F1-score of 82.42%, indicating a balanced performance in delivering accurate and relevant recommendations. Furthermore, the integration of Fuzzy MCDA with user-centered design ensures that the recommendation system remains adaptable to evolving tourist preferences. This framework demonstrates the importance of integrating flexible, user-centered recommendations into tourism to meet evolving visitor needs effectively.

Keywords: Fuzzy TOPSIS, tourism recommendation system, multi-criteria decision analysis, GIS, sustainable tourism, user preferences

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INTRODUCTION

Tourism, a multifaceted industry, significantly contributes to global economies, cultures, and environments. It encompasses a range of activities, including leisure travel, business trips, and cultural explorations, drawing millions of people to various destinations worldwide. Beyond driving economic growth by generating revenue and creating jobs, tourism fosters cultural exchange and understanding (UNWTO, 2020). However, its impact on the environment and local communities necessitates careful planning and management to ensure sustainable development. According to the World Tourism Organization, tourism is a substantial component of non-commodity international trade, ranking as the world's third-largest export category and the top export product for many wealthy countries. It has one of the largest multiplier effects on the economy, adding value to industries like as transportation, trade, services, construction, and building materials production (Chalkiadakis et al., 2023). Moreover, tourism generates substantial socio-economic benefits, including increased employment, income growth, and the development of entrepreneurial culture (Gamidullaeva et al., 2023).

The tourism industry increasingly utilizes technology to enhance service efficiency, improve the tourist experience, and boost customer satisfaction. Innovations such as digital marketing and online booking platforms have made travel more accessible and stress-free while effectively promoting destinations (Xu & Gursoy, 2021; Feng et al., 2022). Among these technologies, Recommender Systems (RS) are pivotal. Recommendation systems utilize statistical and knowledge discovery techniques to recommend things based on user preferences and behaviour. Recently, they were used in the tourism business to recommend destinations to travellers (Forouzandeh et al., 2021). By analyzing user data, RS offer personalized recommendations, enhancing destination competitiveness and fostering deeper interactions between tourists and their surroundings (Hanafiah & Zulkifly, 2019; Solano-Barliza et al., 2023; Isinkaye et al., 2015). In today's digital age, RS are essential tools for recommending destinations, accommodations, and activities based on user preferences, behaviors, and patterns. They address the common reliance on others' experiences and recommendations in unfamiliar or information-rich environments (Solano-Barliza et al., 2024)]. Integrating Geographic Information Systems (GIS) with

* Corresponding author

recommender systems adds a spatial dimension, allowing for consideration of geographic and environmental factors. This combination supports a more comprehensive approach to tourism management, promoting lesser-known destinations and helping to distribute tourist traffic more evenly (Alhijawi & Kilani, 2020). GIS techniques were used to create explanatory variable maps GIS techniques were employed to create maps illustrating the influence of various factors in different applications (Sangpradid, 2023; Waiyasusri et al., 2023; Fallah et al., 2023). For example, factors such as the distance from major roads, forest areas, institutional land, and elevation were considered. The data for each factor was converted into raster format, enabling detailed spatial analysis (Aunphoklang et al., 2021). To enhance the decision-making process, Multicriteria Decision Analysis (MCDA) can be integrated with recommender systems. MCDA is a method designed to evaluate complex decisions that involve multiple, often conflicting, criteria (Prasertsri & Sangpradid, 2020). It employs frameworks and methods that combine quantitative, qualitative, and sometimes contradictory information, along with stakeholder input, to support decision-making. MCDA is adaptable to different contexts, as it aligns with specific user goals, scenarios, and alternative management decisions, incorporating a system for evaluating these alternatives (Cegan et al., 2017). GIS techniques play a crucial role in analyzing and visualizing spatially referenced data, while MCDA provides a structured approach for addressing decision problems and assessing various alternatives (Malczewski, 2006).

In the context of tourism, MCDA can help in balancing various factors such as cost, convenience, environmental impact, and personal preferences when generating recommendations. The characteristics of the MCDA process helps analysts implement the process effectively and recommend appropriate methods, enhancing traceable and categorizable development of decision support systems (Cinelli et al., 2020). By combining MCDA with recommender systems, tourism services can better address the complexities of decision-making in tourism planning. For instance, when tourists are choosing a destination, MCDA can weigh factors like cultural interest, safety, cost, and environmental sustainability, ensuring that the recommendations not only match individual preferences but also align with broader tourism development goals. Moreover, when used alongside GIS, this approach can optimize travel routes, identify strategic investment areas, and improve resource allocation, leading to a more sustainable and balanced for ecotourism and tourism industry (Kaymaz et al., 2021). A multi-criteria recommender system offers a deeper understanding of user preferences by factoring in the underlying attributes that influence choices. Therefore, incorporating additional insights into each user’s preferences can improve the accuracy of the recommendations, leading to more personalized and precise suggestions (Zhuang & Kim, 2021).

MCDA, also known as Multi-Criteria Decision-Making (MCDM), has been increasingly applied in tourism to improve decision-making by evaluating and ranking options based on multiple factors. This structured approach supports complex decision-making scenarios, which is especially useful in tourism. Methods such as Fuzzy MCDA and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) are frequently utilized to enhance accuracy and relevance in tourism recommendations. Vatankhah et al. (2023) highlighted that MCDM techniques provide structured solutions to hospitality and tourism (H&T) challenges, helping to minimize decision risks. Their findings reveal a growing trend in applying MCDM, particularly Fuzzy MCDA, within H&T, although certain techniques remain underutilized, with some areas seeing repetitive applications. Kwok & Lau (2019) introduced a Vague Set TOPSIS modification for hotel ranking, addressing limitations in conventional TOPSIS by enhancing users' ability to express nuanced preferences. Similarly, Putra et al. (2022) applied a Best-Worst Method (BWM) combined with TOPSIS to select tour guides in the Guidemu app, achieving high recommendation accuracy and expert alignment. Dawi et al. (2021) demonstrated that TOPSIS can support both personalized and group-based destination recommendations, with strong correlations between system recommendations and user choices. Despite these advances, studies call for further customization options in MCDA-based systems to better accommodate individual preferences. Modified TOPSIS approaches partially address this, though additional improvements are needed to enhance overall user satisfaction.

The National Tourism Development Plan of Thailand, Phase 3 (2023-2027), envisions comprehensive and inclusive tourism development over a five-year period, with the goal of driving resilience and sustainable growth in the tourism sector. The vision outlined in this plan is: “Tourism in Thailand is an industry that prioritizes value, demonstrates adaptability, fosters sustainable growth, and promotes inclusivity.” This strategic plan emphasizes that tourism should contribute meaningfully to the economy and society, while upholding environmental responsibility and fostering community engagement (National Tourism Policy Committee, 2024). Singtuen & Galka (2024) discuss a creative approach to sustainable tourism by integrating cultural, geotourism, and gastronomic elements to enrich the tourist experience, promote local culture, boost community income, and preserve the environment. This aligns with the Sustainable Development Goals (SDGs), fostering cultural exchange and creativity. In the context of environmental sustainability, Choosuk et al. (2024) focus on community-driven marine debris management to tackle waste challenges brought about by tourism and population growth, emphasizing sustainable practices that respect ecological balance and engage the community. Meanwhile, Lee-anant & Rungreaung (2024) provide insights into enhancing service quality in small boutique hotels to attract domestic workcation tourists, supporting the development of a tourism ecosystem that is responsive to changing market demands. The plan underlines the importance of promoting tourism as a means to strengthen the economy, preserve Thailand’s rich cultural heritage, and improve the quality of life for communities, demonstrating that a well-managed tourism industry can be a powerful driver of national progress.

The aim of this study is to develop a spatial tourism recommendation system that utilizes Fuzzy TOPSIS alongside MCDA to improve the accuracy and relevance of tourism recommendations. This study has two primary objectives: (1) to create a recommendation system based on Fuzzy TOPSIS that integrates expert input, tourist behavior data, and survey feedback to produce precise, targeted recommendations, and (2) to design a system that empowers tourists to make personalized destination choices through a recommendation process that accommodates diverse user preferences.

MATERIALS AND METHODS

Study area

Maha Sarakham province plays a key role in the development of cultural tourism, offering immense potential through its rich history, culture, and unique local wisdom. Attractions such as Phra That Na Dun, Ku Santarat, and the Ancient House Museum showcase this heritage. Consequently, developing a tourism recommender system is crucial, as it provides personalized recommendations, enhances tourist experiences, and promotes sustainable development by distributing visitors efficiently. Furthermore, the province, located between latitudes 15.43º to 16.63º N and longitudes 102.72º to 103.54º E, with a population of 963,047, features a low elevation and is bounded by low hills (Sangpradid & Aroonsri, 2023), making it well-suited for geographic and tourism studies. Additionally, Maha Sarakham is home to historical sites with remnants from the Khmer and Dvaravati periods, as well as a rich culinary history of traditional foods originating from these eras (Jecan et al., 2021). Preserving and promoting these assets, particularly through educational integration, could support tourism growth by blending cultural storytelling with local learning. This approach broadens the tourism landscape, appealing to both cultural heritage enthusiasts and visitors interested in the region's historical cuisine and traditions.

METHODOLOGY

This research develops a spatial tourism recommendation system by utilizing MCDA, GIS, and Fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution). Fuzzy TOPSIS is employed to effectively manage uncertainties and subjectivities inherent in user preferences, thereby providing a flexible and nuanced decision-making process for generating tourism recommendations. GIS introduces a vital spatial dimension, allowing the system to incorporate location-based criteria, while MCDA ensures a balanced consideration of multiple factors, thereby personalizing recommendations that are both sustainable and aligned with tourism development goals. The research follows a four-step methodology as in Figure 1.

(1) Data Collection: Key data related to tourism, geography, and user preferences are gathered for Maha Sarakham province, which serves as the case study area. This data is structured to fit both the Fuzzy TOPSIS and GIS frameworks, enabling a combination of qualitative and quantitative analysis.

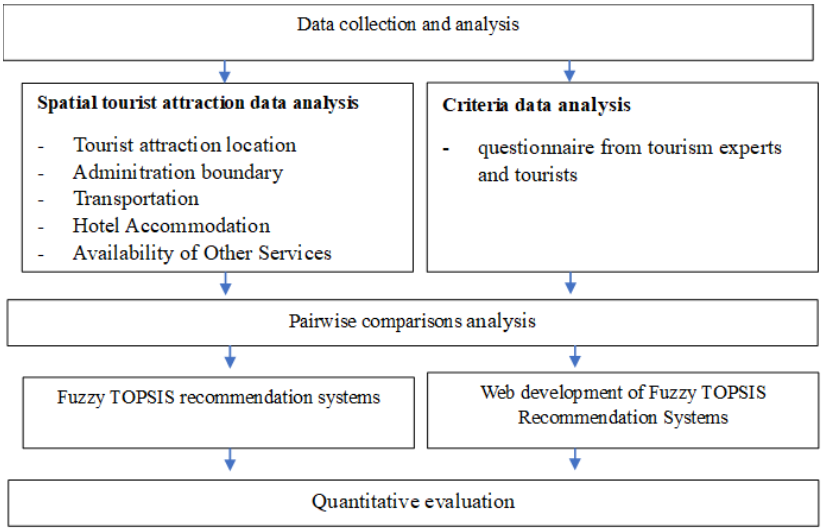

Figure 1. Research framework

(2) Criteria Selection and Fuzzification: In this study, a set of ten decision-making criteria was identified to evaluate and recommend tourism destinations effectively. These criteria are essential for understanding the multifaceted needs of tourists and include: Accessibility to the Site: The ease with which tourists can reach the destination. Availability of Restaurants: The presence of dining options within proximity to the tourist site. Transportation Services: The availability of shuttle services or public transportation for tourists. Accommodation Services: Quality and availability of hotels or lodging near the site. Cafes and Refreshment Places: The presence of coffee shops or cafes in the vicinity. Parking Facilities: Availability of adequate parking for visitors. Safety Services: Access to security services for ensuring tourist safety. Proximity to Hospitals: The closeness of medical facilities for emergencies. Proximity to Police Stations: The presence of local law enforcement to ensure safety. Cost Considerations: The overall cost associated with traveling and visiting the site (including entrance fees). To address the inherent uncertainty in user preferences regarding these criteria, a fuzzification process was implemented. Each criterion was represented using fuzzy logic, allowing qualitative assessments such as "good accessibility" or "reasonable cost" to be quantified. Membership functions were established for each criterion to facilitate a nuanced evaluation that reflects the varying degrees of user satisfaction and preference.

(3) Fuzzy TOPSIS Application: Next, based on how closely the options (activities or locations) resemble the ideal answer, Fuzzy TOPSIS is used to rank them. This approach includes (Prasertsri & Sangpradid, 2020).

- Constructing a decision matrix with the fuzzified data for each criterion.
- Determining the fuzzy positive ideal solution (FPIS) as well as the fuzzy negative ideal solution (FNIS).
- Calculating the separation between FPIS and FNIS for each option.

- The proximity coefficient, which gauges how near each option is to the ideal answer, is used to rank the options.

(4) GIS Integration and Spatial Analysis: GIS tools integrate spatial data with the Fuzzy TOPSIS results. This integration ensures that spatial attributes such as proximity to tourist attractions, accessibility, and environmental impact are considered alongside user preferences. The combination of Fuzzy TOPSIS and GIS yields personalized, location-aware tourism recommendations that promote sustainable tourism by effectively distributing tourists and highlighting lesser-known attractions.

Data Collection and Data Analysis

The data collection process is essential to the success of the Fuzzy TOPSIS and GIS-based tourism recommendation system. The following types of data are gathered from both primary and secondary sources:

(1) Geospatial Data: Geographic information such as elevation, land use, proximity to major roads, and tourist attractions are collected from government databases, satellite imagery, and open-source platforms. These data points are converted into a format compatible with GIS, allowing for detailed spatial analysis.

(2) Tourism Data: The data collection process was designed to gather relevant information related to the ten criteria identified above. The following methods were employed:

Surveys: A survey targeting tourists visiting Maha Sarakham province was conducted. Questions focused on user experiences concerning each of the ten criteria, allowing for a qualitative understanding of tourist preferences.

Site Visits: Direct observations were made at selected tourist sites to assess the availability and quality of services related to the criteria.

Secondary Data Sources: Information regarding accommodations, restaurants, and safety services was collected from local tourism authorities and business directories.

The collected data was then processed and integrated into the Fuzzy TOPSIS framework for further analysis. The data is compiled and processed into a decision matrix for the Fuzzy TOPSIS analysis after it has been collected. The spatial data is integrated into GIS for further analysis and visualization, ensuring the final recommendations are both contextually and geographically relevant. The data analysis gathers opinions from tourism experts and tourists on the criteria used for evaluating tourist sites. The feedback was collected through a survey of 250 respondents and analyzed using the scale of pairwise comparisons method, which involves comparing criteria in pairs to determine the relative importance of each criterion when evaluated against others. Table 1 presents the results of this analysis, showing which criteria are considered more important according to the respondents. The scale of pairwise comparisons technique enables systematic analysis and establishes a ranking of the various criteria, revealing the factors that most influence tourists' choices in selecting destinations.

Table 1. Analysis of criteria for evaluating tourist sites based on expert and tourist opinions using the scale of pairwise comparisons (Source: Prasertsri & Sangpradid, 2020)

Definition	Intensity of importance
Equal Importance	1
Weak or Slight	2
Moderate Importance	3
Moderate Plus	4
Strong Importance	5
Strong Plus	6
Very Strong	7
Very, very Strong	8
Extreme Importance	9

MCDA for Recommendation Systems

Multi-Criteria Decision Analysis (MCDA) encompasses a set of methodologies designed to evaluate complex decision-making scenarios involving multiple, often conflicting criteria. MCDA has been extensively applied in recommendation systems to enhance their capacity to provide tailored suggestions by considering a range of factors and user preferences. Rather than relying on a single criterion (e.g., user ratings), MCDA enables recommendation systems to incorporate various dimensions such as cost, quality, user preferences, and contextual factors, thereby enhancing decision support capabilities. According to the MCDA process greatly influences decision outcomes by focusing on model building and criteria selection, which establish the value concerns for assessing alternative options (Angelis & Kenavos, 2017), thereby improving decision-making in complex environments through structured evaluations of qualitative and quantitative data (Roy, 1996). In the context of recommendation systems, MCDA enables more nuanced recommendations by accounting for the complexities inherent in real-life decisions. For instance, Benítez et al. (2020) employed MCDA techniques in e-commerce recommendation systems to rank products according to multiple criteria such as price, user reviews, and delivery time. Such systems aim to enhance the decision-making process by enabling more sophisticated recommendations aligned with the diverse needs and preferences of users.

Recommendation Systems

Recommendation systems have emerged as efficacious tools to assist users in navigating substantial volumes of information, offering personalized suggestions based on user data. These systems employ a range of methods, such as content-based filtering, hybrid techniques, and collaborative filtering. With the premise that users who have previously shown a preference for a particular thing would do so again in the future, collaborative filtering makes suggestions based on user-item interaction data. Content-based filtering makes recommendations for products that are comparable to those the user has already shown they enjoy based on the features of the item. Hybrid systems combine multiple recommendation techniques to enhance accuracy. Recommendation systems have found application across diverse domains, from e-commerce and entertainment to tourism and healthcare. According to Ricci et al. (2015), recommendation engines examine user behavior, interests, and exchanges to propose goods or services that users are probably to use. In the tourism sector, for instance, recommendation systems analyze user data to propose travel destinations, accommodations, and activities based on user interests, thereby facilitating more personalized and satisfying travel experiences.

Multi-Criteria Recommender Systems

Multi-Criteria Recommender Systems (MCRS) extend the traditional recommendation system framework by incorporating multiple decision criteria into the recommendation process. Traditional recommendation systems typically focus on a single rating value, such as the user's overall satisfaction with a product or service. MCRS, however, consider multiple dimensions such as quality, cost, availability, and user preferences, thereby enabling a more comprehensive evaluation. Adomavicius & Kwon (2011) posit that MCRS offer a more balanced recommendation output by integrating various criteria that influence user decisions. For instance, in a hotel recommendation scenario, an MCRS might consider criteria such as room quality, price, location, and user ratings. This approach results in recommendations that align more closely with the user's diverse preferences.

TOPSIS in Multi-Criteria Recommender Systems

TOPSIS is a widely utilized MCDA method in multi-criteria recommender systems. In order for TOPSIS to function, solutions should display the maximum separation from the negative ideal solution as well as the minimum separation from the ideal solution (Prasertsri & Sangpradid, 2020). This methodology is predicated on the principle that the recommended option should be as proximate as possible to the optimal outcome and as distant as possible from the least favorable scenario. According to Hwang & Yoon (1981), TOPSIS demonstrates efficacy in ranking alternatives within multi-criteria decision-making contexts, rendering it particularly applicable for recommendation systems where multiple attributes, such as cost, quality, and user preferences, must be balanced. Recent studies, applied TOPSIS in tourism recommendation systems to rank destinations based on multiple criteria, including distance, travel time, entrance fees, and cleanliness. It ranks attractions to help users make informed decisions (Ubaidillah & Dwidasmara, 2020; Abbasi-Moud et al., 2021; Forouzandeh et al., 2022). TOPSIS is a MCDM method designed to rank and select options from a set of alternatives. TOPSIS evaluates each alternative by measuring its distance from an ideal solution (best possible outcome) and a negative-ideal solution (worst possible outcome). The alternative closest to the ideal solution and farthest from the negative-ideal solution is considered the best choice. Steps in TOPSIS (Prasertsri & Sangpradid, 2020):

(1) Construct Decision Matrix: List alternatives and criteria with performance scores.
(2) Normalize Matrix: Standardize values to make criteria comparable.
(3) Apply Weights: Multiply each normalized score by the importance weight of its criterion.
(4) Identify Ideal Solutions:
a. Ideal solution: Best values for each criterion.
b. Negative-Ideal solution: Worst values for each criterion.
(5) Calculate Distances: Measure each alternative’s distance to the ideal and negative-ideal solutions.
(6) Calculate Relative Closeness: Compute how close each alternative is to the ideal solution.
(7) Rank Alternatives: Rank based on relative closeness; the higher the score, the better the alternative.

Fuzzy Logic in Multi-Criteria Recommender Systems

Fuzzy logic, introduced by Zadeh (1965), addresses uncertainty and vagueness in decision-making processes, rendering it a valuable tool in multi-criteria recommender systems. This approach extends binary decision-making processes by allowing intermediate values between absolute truth and falsehood. Within the context of recommendation systems, fuzzy logic facilitates the management of ambiguity in user preferences and the imprecise nature of certain criteria. Fuzzy Multi-Criteria Decision Analysis (Fuzzy MCDA) has been employed to generate more accurate and personalized recommendations by capturing the uncertainty inherent in user preferences. Osman et al. (2017) demonstrated the efficacy of, wherein fuzzy logic to search and recommend food based on taste, user preference, and other parameters, providing better results than existing systems. The incorporation of fuzzy logic into Multi-Criteria Recommender Systems (MCRS) enables the provision of more flexible recommendations that more accurately reflect the nuanced nature of user preferences.

Fuzzy TOPSIS in Recommendation Systems

Fuzzy logic is used in fuzzy TOPSIS, a MCDM technique, to address the subjectivity and ambiguity that come with weighing options against a range of criteria. This method is very helpful in complex decision-making circumstances because it uses fuzzy numbers, or linguistic rating variables, to evaluate the options according to each criterion (Prasertsri & Sangpradid, 2020). Fuzzy TOPSIS uses the strengths of both fuzzy logic and TOPSIS to handle ambiguity in MCDM. In this method, fuzzy sets are utilized to represent ambiguous or imprecise user preferences, which are then integrated into the TOPSIS framework to rank options. Fuzzy TOPSIS is a powerful decision-making tool that leverages fuzzy logic to handle uncertainty and imprecision, making it suitable for complex real-world applications. By integrating subjective and objective criteria and employing advanced fuzzy sets, it delivers robust and reliable recommendations across various domains. This method's ability to reduce uncertainty and information loss in group decision-making further enhances its effectiveness, making it a preferred choice for many decision-making scenarios (Mathew et al., 2020; Hatami-Marbini & Kangi, 2017; Rashidi & Cullinane, 2019). Studies such as Forouzandeh et al. (2022) have effectively used fuzzy TOPSIS model effectively recommends the best tourist spots for users, improving their decision-making process in the tourism industry. The inclusion of fuzzy logic into TOPSIS enables a flexible decision-making paradigm, which is especially beneficial in instances where consumer preferences. An outline of the steps in Fuzzy TOPSIS (Prasertsri & Sangpradid, 2020)**:**

1) Define fuzzy decision matrix: identify alternatives and criteria and represent the ratings of each criterion and alternative as fuzzy numbers (triangular fuzzy numbers).
2) Normalize fuzzy decision matrix: Convert all values to a comparable scale, considering the fuzzy nature of each criterion.
3) Apply weights to criteria: Assign a fuzzy weight to each criterion, reflecting its importance.
4) Determine fuzzy ideal solutions: Fuzzy positive-ideal solution (FPIS): The best values for each criterion across alternatives. Fuzzy negative-ideal solution (FNIS): The worst values for each criterion across alternatives.
5) Calculate distances to fuzzy ideal solutions: Compute the distance of each alternative to the FPIS and FNIS, using a distance measure (e.g., Euclidean distance) suitable for fuzzy numbers.
6) Calculate relative closeness coefficient: For each alternative, calculate the relative closeness to the FPIS. This is done by dividing the distance to the FNIS by the sum of distances to both FPIS and FNIS.
7) Rank alternatives: Rank the alternatives based on their relative closeness coefficient. The higher the value, the closer the alternative is to the ideal solution, and thus, the more preferable it is.

Quantitative Evaluation

Quantitative evaluation focuses on measuring outcomes that can be expressed numerically, such as the accuracy and efficiency of the recommendation system. Metrics like Precision, Recall, and F1-Score are commonly used for this purpose (Chompoosri et al., 2024; Arif et al., 2021). The following methods can be employed: Precision: Measures the percentage of recommended tourist destinations that users actually chose to visit. Recall: Measures the percentage of tourist destinations selected by users from those that should have been recommended. F1-Score: Represents the weighted average between Precision and Recall to assess the balance between accurate and comprehensive recommendations.

$$Precision = \frac{TP}{TP+FP}; \quad Recall = \frac{TP}{TP+FN}; \quad \mathrm{F1-Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Where TP represents the number of correctly recommended items, FP represents the number of incorrectly recommended items, and FN represents the number of relevant items that were not recommended by the system according to test users.

RESULTS AND DISCUSSION

Overview of Survey Responses

A total of 250 surveys were collected from tourism experts and tourists visiting Maha Sarakham province. The purpose of the survey was to evaluate ten key criteria influencing the selection of tourist destinations. Respondents assigned importance scores to each criterion using a rating scale from 1 to 9.

Table 2. Summarizes the average scores assigned to each criterion based on the survey results

Criterion	Score
1. Accessibility to the site	9
2. Availability of Cafés and Coffee Shops	7
3. Shuttle Service	1
4. Hotel Accommodation	3
5. Proximity to Cafés and Coffee Shops	7
6. Parking Facilities	5
7. Safety Services	9
8. Proximity to Hospitals	3
9. Proximity to Police Stations	3
10. Cost Considerations (Travel and Entrance Fees)	5

The results from Table 2 indicate that different criteria carry varying levels of importance for tourists when selecting a destination. The scores are based on a rating scale from 1 to 9, where higher numbers indicate greater significance. Highest rated criteria: Accessibility to the site and safety services both received the highest score of 9, emphasizing that ease of travel and security are the most critical factors influencing tourist decisions. Tourists prioritize destinations that are easy to access and ensure their safety. The availability of cafés and coffee shops and proximity to cafés and coffee Shops also scored relatively high, with a score of 7. This suggests that dining options play a significant role in the overall tourist experience and decision-making process. Moderately rated criteria: Parking facilities and cost considerations (Travel and entrance fees) received moderate scores of 5. While these aspects are relevant, they are not as crucial as accessibility, safety, and dining options.

Lowest rated criteria: The shuttle service received the lowest score of 1, indicating that it is the least important criterion for tourists. Tourists appear to place minimal importance on the availability of shuttle services when selecting destinations. Hotel accommodation, proximity to hospitals, and proximity to police stations each scored 3, showing that while these factors are considered, they are not primary concerns for tourists in this study. The results regarding tourist decision-making show significant alignment with recent research. Accessibility and safety, ranked as the highest criteria, confirm the findings of studies like those by Choi et al. (2020), which underscore the increasing importance of these factors in shaping tourist behavior. The high rating for dining options (cafés) supports research by Provenzano & Baggio (2020), highlighting the growing role of gastronomic experiences in destination choices. The lower importance of shuttle services and accommodations echoes a trend towards more individualized travel options, as noted in recent studies on evolving tourist preferences.

Fuzzy TOPSIS Analysis of the Recommendation System

The collected data was processed using the Fuzzy TOPSIS method, ranking the potential tourist destinations based on their alignment with the identified criteria and weights. The following table summarizes the results. From Table 3, which ranks tourist attractions based on the Fuzzy TOPSIS analysis, it is revealed that Phra that Na Dun is the top-ranked tourist attraction in Maha Sarakham, with the highest score of 0.00362, demonstrating strong alignment with key decision criteria such as accessibility and safety. Wat Puttha Wanaram follows closely with a score of 0.00108, reflecting significant tourist interest and a close match to the preferred factors. Mid-ranked attractions like Phra Yuen Mongkhon Buddha Image and Kae Dam Wooden Bridge, scoring 0.00045 and 0.00025 respectively, exhibit moderate appeal, suggesting that they meet some, but not all, important criteria.

Table 3. Rankings of tourist attractions based on Fuzzy TOPSIS analysis

No.	Tourist Attraction	Score	Rank
1	Phra that Na Dun	0.00362	1
2	Wat Puttha Wanaram	0.00108	2
3	Phra Yuen Mongkhon Buddha Image	0.00045	3
4	Kae Dam Wooden Bridge	0.00025	4
5	Khong Kut Wai Fish Sanctuary	0.00022	5
6	Wat Nong Hu Ling	0.00019	6
7	Phra Buddha Ming Mueang	0.00017	7
8	Maha Sarakham University Museum	0.00016	8
9	Wat Mahachai	0.0001	9
10	Ku Santarat	0.00007	10
11	Ku Mahathat	0.00006	11
12	Kaeng Leng Chan	0.00005	12
13	Kosamphi Forest Park	0.00004	13
14	Ban Chiang Hian Museum	0.00003	14
15	Chi Long Forest Park	0.00003	15

Lower-ranked sites, such as Ban Chiang Hian museum and Chi Long forest park, received the lowest scores, indicating lesser interest from tourists based on the evaluated criteria. These findings suggest that Phra that Na Dun and Wat Puttha Wanaram are the most desirable destinations, while the analysis can help guide tourism development strategies to enhance the appeal of mid- and lower-ranked attractions. Figure 2 shows the geographic location of a specific tourist attraction, highlighting its position based on the results of the Fuzzy TOPSIS recommendation system.

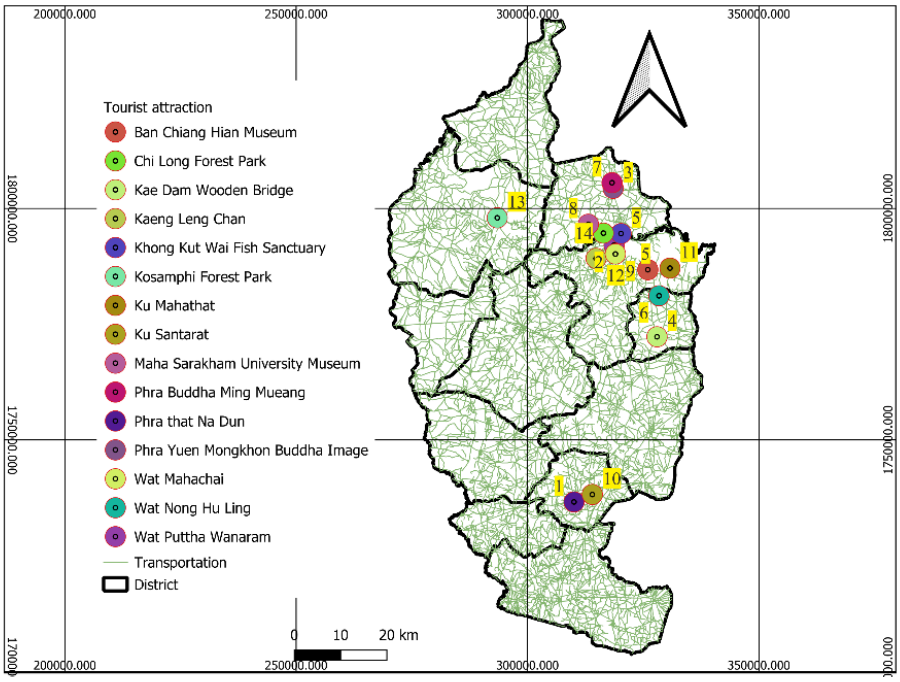

Figure 2. Shows the geographic location of a specific tourist attraction (Source: authors)

Results of the Survey on the Recommendation System

The survey aimed to evaluate the effectiveness of the recommendation system for tourists, focusing on various performance aspects. Table 4 shows the evaluation of the Recommendation System by tourists. The analysis of results reveals the following: Decision-Making Capability: The system received a high mean score of 4.67 for its ability to make appropriate decisions regarding tourist options, indicating strong performance in this aspect. Accessibility: With a score of 4.58, the system effectively addresses the accessibility of tourist destinations, making it a valuable tool for users. Overall Effectiveness: A rating of 4.42

suggests that tourists view the system as a reliable alternative when planning their trips, reinforcing its overall utility. User Satisfaction: The criterion related to matching attractions with user preferences scored 4.58, reflecting high satisfaction among users regarding the relevance of recommendations. Ease of Use: The system scored 4.67 in usability, highlighting its intuitive interface and variety of options available to tourists, contributing to an overall positive user experience. The evaluation findings indicate that the recommendation system is well-received by tourists, consistently scoring high across various criteria. Its strengths lie in decision-making capabilities and ease of use, making it a reliable tool for enhancing the travel experience. Continued improvements and updates could further increase its effectiveness and overall user satisfaction.

Table 4. Evaluation of the Recommendation System by Tourists

No.	Criterion	Mean	Std.	Level
1	Decision-Making Capability	4.67	0.85	Good
2	Accessibility	4.58	0.86	Good
3	Overall Effectiveness	4.42	0.86	Good
4	User Satisfaction	4.58	0.64	Very Good
5	Ease of Use	4.67	0.47	Very Good

Quantitative Evaluation of the Recommendation System

The performance of the recommendation system was quantitatively assessed using the precision, recall, and F1-score metrics. Below is a summary of the outcomes. Table 5 presents the definitions of key performance metrics used in evaluating the recommendation system: Precision: Precision gauges how well the system predicts good outcomes.

A precision score of 85% indicates that 85% of the recommendations provided were relevant to the users. Recall: Recall gauges how well the system can locate all pertinent recommendations. A Recall score of 80% means that the system successfully identified 80% of all available relevant recommendations. F1-Score: An F1-Score of 82.42% suggests that the system effectively balances accuracy and coverage, ensuring that users receive both precise and comprehensive recommendations. Quantitative Evaluation: The quantitative evaluation demonstrates that the recommendation system performs effectively, with high Precision and Recall values, leading to a strong F1-Score.

These data demonstrate how the system may minimize irrelevant recommendations while increasing useful ones. Continuous monitoring and refinement of the system will help maintain and potentially improve these performance metrics.

Table 5. Quantitative Evaluation of the Recommendation System

Metric	Value
Precision	85%
Recall	80%
F1-Score	82.42%

CONCLUSION

The implementation of Fuzzy MCDA through the Fuzzy TOPSIS method has proven to be a valuable approach in developing an effective tourism recommendation system. The findings from the survey and subsequent analysis provide critical insights into how this method can enhance the decision-making processes for tourists and improve their overall travel experiences. The survey results highlighted the importance of specific criteria in influencing tourists' choices of destinations. Notably, accessibility to the site and safety services emerged as the most significant factors, each receiving a maximum weight of 9. This underscores the necessity for destinations to prioritize ease of access and security measures to attract tourists. The high importance assigned to restaurants and coffee shops indicates that modern travelers not only seek cultural and natural attractions but also value social and culinary experiences as integral components of their visits.

Incorporating these preferences into the recommendation system enhances its relevance and usability. By aligning the system's suggestions with the criteria that matter most to users, the Fuzzy TOPSIS method effectively narrows down options to those that truly fit the tourists' desires. The Fuzzy TOPSIS method's ability to rank tourist attractions based on multiple criteria demonstrates its effectiveness as a decision-making tool in the tourism sector. The rankings generated where Phra that Na Dun and Wat Puttha Wanaram were identified as top destinations offer actionable insights for tourism stakeholders.

These findings suggest that focusing promotional efforts and resources on these attractions could yield higher visitor satisfaction and engagement. The low scores associated with attractions like Ban Chiang Hian Museum and Chi Long Forest Park reveal opportunities for development. Stakeholders can explore enhancing these sites' features or services, possibly through infrastructural improvements, increased marketing, or additional amenities. This targeted approach can help diversify tourism offerings and stimulate local economies. The effectiveness of the recommendation system, as indicated by high scores across various performance metrics (mean scores exceeding 4.5), reflects users' satisfaction with its usability and decision-making capabilities. The system's design to match attractions with user preferences demonstrates a user-centered approach that enhances its overall utility. High precision (85%) and recall (80%) scores indicate that the system reliably identifies relevant attractions while minimizing irrelevant suggestions. This capability is crucial in fostering trust among users, as they can depend on the system to deliver accurate and tailored recommendations. Moreover, the commendable F1-Score (82.42%) emphasizes a balanced performance in both identifying relevant options and ensuring their accuracy. The findings suggest that integrating Fuzzy MCDA methods like Fuzzy TOPSIS into tourism recommendation systems can significantly enhance user experience and satisfaction. Future iterations of the system could benefit from incorporating additional factors such as user feedback and dynamic data (e.g., real-time availability, seasonal attractions) to further refine recommendations.

Additionally, Longitudinal studies that evaluate user experiences over time might offer additional information about the system's efficacy and potential areas for development. Leveraging machine learning techniques to adapt the recommendation system based on user interactions could create a more personalized experience, aligning recommendations even more closely with individual preferences. Limitations of Using a Fuzzy TOPSIS approach are the effectiveness of Fuzzy TOPSIS can be significantly influenced by the sensitivity of its results to criteria weights. Even small changes in these weights may alter the rankings, potentially affecting the consistency and reliability of the recommendations. Additionally, since tourist preferences can shift over time due to trends or individual factors, the static nature of certain criteria in Fuzzy TOPSIS may limit its ability to capture these evolving preferences accurately. To address these limitations, improving data collection methods, refining fuzzy criteria definitions, and incorporating more dynamic or hybrid models could enhance the adaptability and accuracy of the recommendation system for destination selection.

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