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RESEARCH ARTICLE

Enhancing Fair Tourism Opportunities in Emerging Destinations by Means of Multi-criteria Recommender Systems: The Case of Restaurants in Riohacha, Colombia

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Abstract

This study addresses the problem of recommending restaurants in emerging tourist destinations, taking into account factors vital in these locations, such as location, safety, price and services. The novel recommendation model is based on the well-known logical scoring of preferences (LSP) methodology. The system considers individual preferences across a hierarchy of criteria. The user can customize the recommender by providing suitability scores and aggregation operators for each criterion. The first contribution is the identification of relevant criteria for the selection of restaurants in emerging destinations and the definition of a new scoring system to manage user preferences regarding types of food. The second contribution of this study is the selection of appropriate conjunctive/disjunctive aggregation operators. The recommender system has been tested in a use case in Riohacha (Colombia), obtaining promising results in a wide range of user profiles.

Keywords Recommender system · Tourism · Decision-making · Multi-criteria · Logic scoring of preferences · Graded logic · Emerging destination

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1 Introduction

Choosing tourism services in a destination can be challenging because of the sheer variety of options available [1], which can be overwhelming for tourists seeking suitable and authentic experiences. In emerging tourist destinations, access to information about the characteristics of products may be difficult due to the lack of proper homogeneous platforms, effective tourist management offices, and customers' online reviews. These limitations on information availability can make decision-making and planning difficult, especially for visitors unfamiliar with the destination, which can also add an additional level of uncertainty and insecurity for tourists when selecting service providers.

Among the various categories of tourism that can be found, such as cultural, religious, health, sports, relaxation, business, and gastronomy, the latter stands out as an essential travel experience. Gastronomy is particularly relevant as an inherent activity for all visitors as, regardless of their main motivation for the trip, they will need to eat during holidays, possibly in restaurants [2]. However, the selection of restaurants may be complicated because the appropriate search involves considering different criteria to select the option that best suits tourists' expectations [3]. The choice is not based only on taste, as many other factors may play a relevant role in the final gastronomic experience. Therefore, a multiple-criteria decision analysis should be performed.

To address these challenges, the tourism sector is incorporating various emerging technological solutions, such as cloud computing, social media, big data, augmented reality, and internet of things (IoT), which contribute significantly to strengthening the competitiveness indicators of tourism destinations [1]. Recommender systems (RS) based on artificial intelligence stand out as a highly innovative and useful solution to provide personalized information to the different kinds of tourists [4, 5]. Moreover, RS can be used to satisfy tourists' changing preferences in different contexts [6]. Given the diversity of tourists' tastes and preferences, it is essential to develop appropriate user profiling models that allow personalization of the offer of tourism products and services, such as restaurants [7]. Most current RS for tourists use machine learning techniques to build models based on a large collection of historical data [1, 8]. Machine learning is highly exploited in collaborative recommender systems, where high-dimensional matrices of user-item data are analyzed to generate a suitable personalized recommendation [9–11]. However, this approach is not viable in small or new destinations due to the lack of such historical data, which must be specific about the site of interest.

An example of an emerging tourism destination that wants to promote services to attract more visitors is Riohacha-La Guajira, Colombia. This area of Colombia is gaining popularity due to its rich natural, cultural, or historical resources, a developing tourism infrastructure, and their relative authenticity and originality compared to more established destinations; however, other emerging destinations are confronted with several issues in order to attract tourism [12]. The problems of such destinations include the lack of consolidated tourism infrastructure, limited promotion and marketing, sensation of insecurity, and lack of international awareness and recognition [13, 14]. In summary, when attempting to develop personalized recommender systems with Artificial Intelligence methods, as in the case of restaurants, the main challenges are as follows:

1. In these emerging tourist destinations, information on the products and services offered by restaurants is not easily accessible to tourists. In particular, regarding the availability of other user's reviews [15]. This lack of data makes it difficult to implement technological solutions that use collaborative approaches, as little information is available on the preferences of tourists in these destinations. A concrete example is shown in Table 1, which presents the number of restaurant reviews in Riohacha on TripAdvisor, comparing it with other tourist cities that share similar characteristics, such as those located in the Caribbean Sea, such as Santa Marta (Colombia), Cartagena (Colombia), and other internationally well-known destinations such as Cancún (México). Table 1 reveals that in the case of Riohacha, the restaurants with the best scores have fewer than 300 reviews, compared to the other more popular destinations that have a higher participation of users in the evaluation of restaurants, reaching 3000 and 4000 (ten times more than the emerging destination of Riohacha).
2. Emerging tourist destinations in less developed countries often face tourism security challenges compared with more developed destinations. These challenges may include theft, scams, lack of security infrastructure, social conflicts, and health risks that tourists may face owing to a lack of knowledge of the social context of the destination[16, 17]. Other common factors in this type of destination are related to price informality in the supply of products and services, especially in the case of restaurants. If these factors are not considered, they can have a negative impact on the tourist experience and, in turn, affect the income generated by tourism at the destination.
3. There is a limited availability of qualitative data about restaurants, such as users' opinions, which help tourists get an overall idea of what a restaurant offers. Therefore, it is convenient to build recommendation models based on restaurant features and meal offers rather than on collaborative techniques. Using approximate reasoning and logical operators, we can represent the human way of selecting restaurants based on a personalized evaluation of restaurant characteristics. Such a system is more flexible and personalized to the user's profile than the usual navigation and Boolean filtering through a website, such as TripAdvisor.

Table 1 Number of reviews of Caribbean tourist destinations

Caribbean tourist destinations	Number of reviews in restaurants
Riohacha (Colombia)	La Trece Bistró (80) Restaurante La Casa del Marisco (285) Restaurante Yotojoro (84)
Santa Marta (Colombia)	Soul Food (390) Lulo (2.055) Restaurant Bar Burukuka (1.042)
Cartagena (Colombia)	Mar de las Antillas (3.430) Inkanto Prime Cartagena (2.952) Buena Vida Marisqueria y Rooftop (4.537)
Cancún (México)	Restaurante Careyes (3.990) Divina Carne (1.667) Navíos Mexican Fusion Seafood (3.559)

These elements are essential for the creation of ICT solutions available online, either on the Web or on mobile phones, which personalize the offer of products and services in restaurants, thus ensuring that the tourist experience is unique and satisfactory.

This personalized online recommendation tool aims to address the social challenges of emerging tourism destinations by promoting equity and improving the quality of life of individuals and communities by fostering the inclusion of local restaurants and small businesses on the same platform as larger and more prestigious ones. Such tools aim to provide them with more visibility and business opportunities, which can contribute to employment generation, local economic development, and preservation of traditional gastronomic culture.

In this sense, the proposed restaurant recommendation system can serve as a platform for the promotion of cultural diversity, social inclusion, and equal opportunities by highlighting the richness of the local cuisine of the destination's host community. In this way, it can contribute to the valorization of cultural identity, as well as having other relevant elements, such as generating a secure recommendation within the emerging tourist destination.

In this paper, we present an innovative proposal based on a multi-criteria evaluation of the preferences of each tourist, aggregated by means of graded conjunctive–disjunctive logic operators that follow a hierarchical criteria structure. A model for a restaurant recommender system was presented and validated in the case of Riohacha, but the proposed recommendation methodology can be tailored to other emerging destinations.

1.1 Related Work

This section provides an overview of the most pertinent literature on the design and implementation of recommender systems for restaurants. A search for open-access articles in the specialized databases Scopus and Web of Science was conducted using the keywords "recommender system", "restaurant", and "multi-criteria" for the period 2010 to 2024 in order to explore the recent use of a multi-criteria holistic evaluation for restaurant's recommendation.

Among the retrieved articles, we observed the emergence of recommender system models combining machine learning (ML) and multi-criteria decision aid (MCDA) techniques, as well as models exclusively grounded in MCDA.

1.1.1 Restaurant Recommendation Based on ML Techniques

An example of employing ML models in this area was the work proposed by Mishra et al. [18]. This study introduced a sophisticated knowledge-based recommendation system aimed at aiding tourists in discovering less prominent restaurants with limited publicity. The system integrates opinions and star ratings from reviews, leveraging classifiers such as Random Forest and Decision Trees to bolster prediction accuracy. Furthermore, the system incorporates clustering techniques. This system tailors the recommendations based on user preferences, restaurant knowledge, and the significance of each criterion. It utilizes a comprehensive dataset sourced from Yelp.com encompassing detailed information on businesses, reviews, users, tickets, tips, and photos, with a specific focus on almost 2.5 million reviews spanning over 21,000 restaurants across the United States. The automated system deploys a variety of ML classifiers, with the random forest classifier achieving an extraordinary accuracy rate of 99.98%.

Alabduljabbar proposed a collaborative restaurant recommendation system in Riyadh, Saudi Arabia [19]. By leveraging user opinions and ratings, the system anticipates individual preferences and tailors' recommendations accordingly. The system incorporates three distinct approaches: non-negative matrix factorization (NMF), singular value decomposition (SVD), and optimized singular value decomposition (SVD++). A substantial dataset of Riyadh restaurants was gathered from Foursquare.com, encompassing a diverse range of restaurant characteristics and attributes. The evaluation results demonstrated the effectiveness of both SVD and NMF in generating recommendations, with a marginal advantage of SVD in terms of root mean square error (RMSE) and slightly superior performance of NMF in terms of mean absolute error (MAE). These findings underscore the efficacy of the collaborative approach by utilizing matrix factorization algorithms to capture intricate relationships between users and restaurants.

Asani et al. introduced a sentiment analysis-based recommender system for restaurant suggestions [20]. This system extracts individuals' food preferences from their comments and recommends nearby open restaurants in alignment with them. The approach employs semantics to cluster food names extracted from users' comments and analyze their sentiments toward them. This methodology encompasses the extraction of food names using natural language processing, followed by sentence-level sentiment analysis using the linguistic enquiry and word count (LIWC) 2007 dictionary and aspect-level sentiment analysis using support vector machines (SVM). Furthermore, contextual information, including time, the user's company, and the user's goal, was utilized to calculate the correlation between restaurant features and user preferences and contexts. The data sources consisted of 100 distinct user reviews collected on TripAdvisor during the first nine months of 2018. The proposed system demonstrated 92.8% accuracy in its recommendations, surpassing previous work in terms of accuracy and recall. The identified areas for improvement involve expanding the system's coverage to encompass a broader range of contexts and user preferences, along with integrating more diverse data sources to enhance the depth of analysis.

An ML model presented by Laksono et al. [21] focuses on data mining restaurant reviews from TripAdvisor, centering on two sentiment analysis techniques (Naïve Bayes and TextBlob) to categorize reviews as positive or negative. The methodology involved collecting restaurant review data from TripAdvisor using web crawling techniques. Data preprocessing steps such as stop word removal were applied. This study achieved an accurate classification of reviews, with an overall accuracy of over 88% in both cases.

Ashfia et al. [22] present a restaurant recommendation system by means of data pre-processing, feature extraction and model training. It uses a public Kaggle dataset called Kzomato, which contains 9552 samples and 21 features. The methodology employed encompasses data collection from restaurant reviews, pre-processing by feature coding, and the use of a bidirectional language model called ALBERT to generate dense vectors, which are later processed by simple recurrent units to capture temporal dependencies. The result obtained is a model that improves the accuracy of recommendations by considering user preferences, which translates to higher user satisfaction by receiving options that align with their tastes.

Sanchez et al. [23] propose a model of recommender system for a food delivery application based on the number of orders placed by customers. The techniques used include a classical nearest-neighbor approach based on the percentage of orders. The data source used was sales transactions stored automatically by the application, eliminating the need for customer questionnaires or ratings. The methodology focuses on identifying customers' preferred restaurants, defined as those that represent at least 10% of a customer's orders. The results show that the system can identify a preferred restaurant in 24% of the cases from a list of 7.7 recommendations, out of a total of 187 available restaurants, confirming the satisfactory performance of the system.

Ahmed et al. [24] develops a restaurant recommendation system in Dhaka city using a machine learning approach. For this purpose, data processing and feature selection techniques were employed using data sources collected from websites, such as Google Maps, Facebook, and Food Panda. The methodology includes data collection and processing, followed by the construction of an ML algorithm that filters and recommends restaurants based on user preferences, such as location, price range, type of food, and ratings. The result is a system that can be integrated into the web or mobile applications to improve the suggestions and performance of food delivery applications in Dhaka.

Prakruthi et al. [25] present a model focusing on a restaurant recommendation system that uses spatial analysis techniques, sentiment analysis, and behavioral pattern analysis to personalize restaurant suggestions to users. The data source used comes from the Zomato dataset, which includes details of over 50,000 restaurants in Bangalore. The result is a system that not only provides personalized recommendations to customers but also offers feasibility reports for potential restaurant owners, helping them to optimize location and operations based on user preferences and market trends.

1.1.2 Integration of ML and MCDA for Restaurant Recommendation

In exploring works that leverage ML and MCDA, Jabreel et al. introduced SentiRank [26], an innovative system that takes into account both the decision-maker's preferences and online public opinions regarding the restaurants to be ranked. This system integrates sentiment information extracted from reviews as an additional set of criteria in the ranking process by utilizing the ELECTRE methodology for ranking alternatives. The methodology employed involves the integration of sentiment information on aspects as new social criteria along with conventional domain criteria. An aspect-based sentiment analysis system was designed and implemented. To identify relevant aspects in a sentence and calculate the polarity of the user sentiment toward each aspect, an SVM was employed. The experiments validated the merit of incorporating sentiment information from reviews into the ranking process, revealing substantial alterations in the rankings when considering social criteria.

Angamuthu and Trojovsky proposed combining MCDA, ML, and deep learning (DL) techniques in a recommender system, aiming to enhance the accuracy of recommendations across various domains, such as movies, products, and restaurants [27]. The methodology involved incorporating advanced techniques to refine recommender systems through sentiment analysis and the inclusion of item properties, such as genres, in a collaborative filtering-based recommender system. Specifically, hybrid deep learning methods have been employed for sentiment analysis. The data used in this study were sourced from three primary platforms available in the Kaggle, TripAdvisor, and Movie databases. The results demonstrate that the integration of sentiment analysis significantly improves the accuracy of the recommendations. Additionally, an enhancement in multi-criteria recommendation coverage was observed with an increase in the number of new item ratings.

Chenbin et al. [28] propose a personalized restaurant recommendation model that combines group correlations and customer preferences to help TripAdvisor.com users find satisfying restaurants. The model employs probabilistic linguistic term set techniques to describe group preferences, taking into account fuzzy and uncertain preferences. The similarity of a new user with groups of customers was calculated using a weighted arithmetic average. The data source used was a real dataset extracted from TripAdvisor.com, and the k-means ML algorithm was used to build customer groups. The methodology includes a case study to validate the proposed model. The results demonstrate that the model can significantly improve the accuracy of personalized restaurant recommendations. The results show that the proposed model outperforms the other three models in terms of recommendation accuracy, exhibiting the lowest RMSE and MAE values. Through fivefold cross-validation and using 20% of the dataset for testing, the model achieves the smallest deviation in customer-restaurant pair predictions.

Yang et al. [29] present the model is a hybrid approach that combines the qualitative analysis of aspect-based sentiment analysis with the quantitative analysis of the matrix factorization MF model to process and integrate data from restaurant ratings and review texts. This model uses deep learning techniques to improve the accuracy and efficiency of personalized recommendations. The data sources employed include restaurant ratings and restaurant review texts. The methodology employed integrated these two data sources into three neural networks. As a result, the proposed model outperformed the existing models in terms of prediction accuracy, as verified by experimental results using the Yelp.com dataset.

1.1.3 MCDA-Based Restaurant Recommenders

Finally, restaurant recommender systems employing MCDA models and techniques have been explored. Ricci et al. [30] designed a graphical user interface to assist event organizers in finding a suitable restaurant for a group. In their methodology, they suggest three recommendation techniques (popularity-based, relevance-based, and criticality-based) to facilitate this task. Each makes distinct assumptions about the available information on group members' preferences and supports different usage patterns. Throughout the application development process, collaborative efforts were undertaken with *the myfood* platform (by Okkam) to enhance their restaurant application. Additionally, complementary decision support functionalities were devised to aid the organizer in making a fair and time-efficient choice. The results demonstrate that this system contributes to decision-making by unveiling the attractiveness of a recommended restaurant to each member of the group.

Hing and Jung proposed two multi-criteria tensor models that concurrently considered the inherent structure and interrelationships among factors, such as users, countries, multi-criteria ratings, and cultural groups, within tourism recommendation processes [31]. These models were assessed using a TripAdvisor dataset comprising 36,795 user reviews of 2000 restaurants in London involving 13,620 users from 120 countries. The experimental results indicate that two of their multi-criteria tensor models outperform the comparative approaches, demonstrating significant improvements in the Mean Absolute Error.

Likewise, Zhang et al. introduced a model [32] designed to assist tourists in making restaurant decisions by leveraging social information from TripAdvisors. This model incorporates fuzzy sets to represent online reviews and utilizes the Bonferroni mean to account for the interdependence between criteria. The dataset, manually collected from TripAdvisor, comprises 14,562 records involving 451 tourists and 4820 restaurants rated on four criteria: food, service, value, and ambience. Given that ratings are based on multiple criteria, the overall prediction is derived by integrating the predictions for each criterion. This study introduces a novel measure of tourist similarity that addresses the limitations of existing measures and handles surplus data in fuzzy environments from a theoretical perspective. The results suggest that the model outperforms models based on the assumption of independent criteria.

Hartanto and Utawa introduced an intelligent decision support model [33], crafted to offer personalized restaurant recommendations tailored to individual preferences. The model incorporates seven parameters: interest, price, location, taste rating, cleanliness rating, facility rating, and halal/nonhalal status. Building the model involves the application of fuzzy logic, cosine similarity distance, and optimization methods, specifically a hybrid Latin hypercube and scaling. Their experiment encompassed 75 restaurants in Jakarta and involved eight customers with data sourced from Google Maps. The model proved to be effective in providing restaurant suggestions for both individual users and groups. The hyper-cube-hill-climbing method provided an optimal decision alternative, particularly for customers aiming to adhere to a budget.

The model presented by Shu et al. [34], which is grounded in linguistic variables, aims to evaluate customer satisfaction on online restaurant review platforms. This methodology encompasses the utilization of linguistic variables, an aggregation model, and a weighting method. The data were obtained from an extensive database of online reviews. Consequently, this study was able to generate customized composite scores, enhance the linguistic comprehension of restaurant ratings, and explore how these ratings evolve based on users' levels of demand. The authors introduced a methodology that facilitates a more nuanced interpretation and customisation of restaurant ratings derived from online reviews, addressing the inherent issue of information loss in traditional fuzzy linguistic approaches. This leads to an improvement in the accuracy and interpretability of results.

A summary of the studies selected for the literature review is provided in Table 2. Two main approaches can be distinguished: those based on machine learning from examples, and those based on evaluating the performance of restaurants with a multi-criteria decision analysis. We can see

Table 2 Summary of works on restaurant recommender systems

References	Use of reviews	ML/MCDA	Techniques	Sentiment analysis	Case study	Source data
[18]	Yes	ML	Random forest and decision tree	No	USA	Yelp
[19]	Yes	ML	Non-negative matrix factorization (NMF), singular value decomposition (SVD), optimized singular value decomposition (SVD++)	No	Riyadh	Foursquare
[20]	Yes	ML	Natural language processing, sentiment analysis, SVM	Yes	Not specified	TripAdvisor
[21]	Yes	ML	Naive Bayes, TextBlob	Yes	Surabaya	TripAdvisor
[22]	Yes	ML	ALBERT (bidirectional language model) and simple recurrent units	Yes	New Delhi, India	Zomato Restaurants Data
[23]	No	ML	KNN	No	–	Orders from a real food delivery application
[24]	Yes	ML	Weight-based scoring and the cosine similarity matrix	No	Dhaka	Google Maps, Facebook y Food Pand
[25]	YES	ML MCDA	Sentiment analysis	Yes	Bangalore	Zomato
[26]	Yes	ML MCDA	Sentiment analysis, ELECTRE	Yes	Tarragona	TripAdvisor
[27]	Yes	ML MCDA	Sentiment Analysis, Collaborative filtering	Yes	Trip-2020 dataset	Kaggle TripAdvisor
[28]	Yes	ML MCDA	Probabilistic linguistic term sets (PLTS) Clustering Averages	Yes	Worldwide	TripAdvisor
[29]	Yes	DL MCDA	MLP (Perceptrón Multicapa) y ABSA (Análisis de Sentimientos Basado en Aspectos)	Yes	Marrakech	TripAdvisor
[30]	Yes	MCDA	Popularity-based, relevance-based, and critiquing-based	No	Not specified	www.okkam.it
[31]	Yes	MCDA	Multi-criteria tensors	No	London	TripAdvisor
[32]	Yes	MCDA	Fuzzy logic, Bonferroni mean	No	Not specified	TripAdvisor
[33]	Yes	MCDA	Fuzzy logic, hyper-cube-hill-climbing	No	Jakarta	Restaurant data Google Maps
[34]	Yes	MCDA	2-tuple linguistic ordered weighted averaging	No	China	Dianping

that all of them use information from customer reviews, and some apply sentiment analysis. This ML approach requires a large dataset of examples to train an accurate prediction model, which is not available in emerging tourist destinations because they are places that do not have a consolidated and sufficient number of visitors at the current date. Moreover, none of the studies delve into the aspects that we propose in our paper, those related to the definition of multiple criteria at different levels of generality, and those exploiting complex logical reasoning operators as the ones proposed in this paper. It is worth mentioning that several recommender systems found in the review have relied on data for the design of their models from the TripAdvisor platform, as we will use in our model.

1.2 Goal and Contributions

The goal of this work is to build a recommender system for restaurants that considers the user's tastes, affordability, and contextual information. The contributions of this paper are the following:

- Identification of relevant criteria and modeling of user preferences by means of predefined suitability degree.

This includes the definition of the FSIS scoring system to represent preferences regarding types of food.

- Proposal of a hierarchical criteria structure with the definition of appropriate aggregation operators using the graded junction/disjunction logic model [35] including asymmetric operations.
- Application and evaluation of proposed recommender system in a case study in Riohacha, Colombia.

The paper is organized as follows: Sect. 2 provides the restaurant recommendation system, an overview of the preliminary concepts and definitions on which our method is based, and the proposed methodology for the construction of the recommendation model (see Fig. 1). Section 3 describes the application of the restaurant recommendation system in Riohacha, an emerging tourist destination in Colombia. Section 4 presents the validation of the model results with experts. Section 5 presents the analysis and discussion of some user profiles used to test the model. Finally, Sect. 6 presents conclusions and future work.

2 Restaurants Recommender System

This section presents the theoretical underpinnings of the proposed recommendation system model. The proposed method is based on multi-criteria decision aiding (MCDA) techniques, as they are a suitable approach to deal with different, possibly conflicting criteria when evaluating a set of alternatives with the final goal of differentiating them from an overall suitability perspective [36].

The two fundamental concepts in the MCDA models are as follows:

1. A finite set of alternatives (or options) to be evaluated, which are the object of the decision, $A = \{a_1, a_2, \ldots, a_n\}$.
2. A finite set of criteria $G = \{g_1, g_2, \ldots, g_m\}$ is used to evaluate and compare the performance of the alternatives in terms of some of the alternative's features, which may be quantitative or qualitative. Importance degree can be associated with each criterion, which can represent either the importance of the criterion or its relative voting power, depending on the type of MCDA method to be used.

Traditionally, MCDA methods assume that all the criteria are defined at a flat common level. However, in some decision problems, it is appropriate to identify several groups of criteria related to the different aspects of the problem. In this case, a hierarchical criteria structure can be defined, and MCDA methods must be able to work following this hierarchy [35, 37, 38].

The MCDA literature distinguishes two main approaches [39]: value-based and relational methods. Value-based methods represent preferences based on the value or suitability. Preferences are quantified using a numerical scale, where each alternative is assigned a value that reflects its perceived suitability, according to specific criteria. The marginal value function $v_i(a_j) \rightarrow [0,1]$ assigns a numerical value to each alternative, representing the subjective suitability degree perceived by the user for alternative a_j in relation to the ith criterion [40]. Therefore, value functions are used to model user preferences. Value functions can also be seen as membership functions that define a fuzzy set that represents the satisfaction of the user with a feature value.

Aggregation operators are then employed to compute an overall suitability for each alternative by merging the marginal suitability values $v_i(a_j)$ [41]. The selection of an

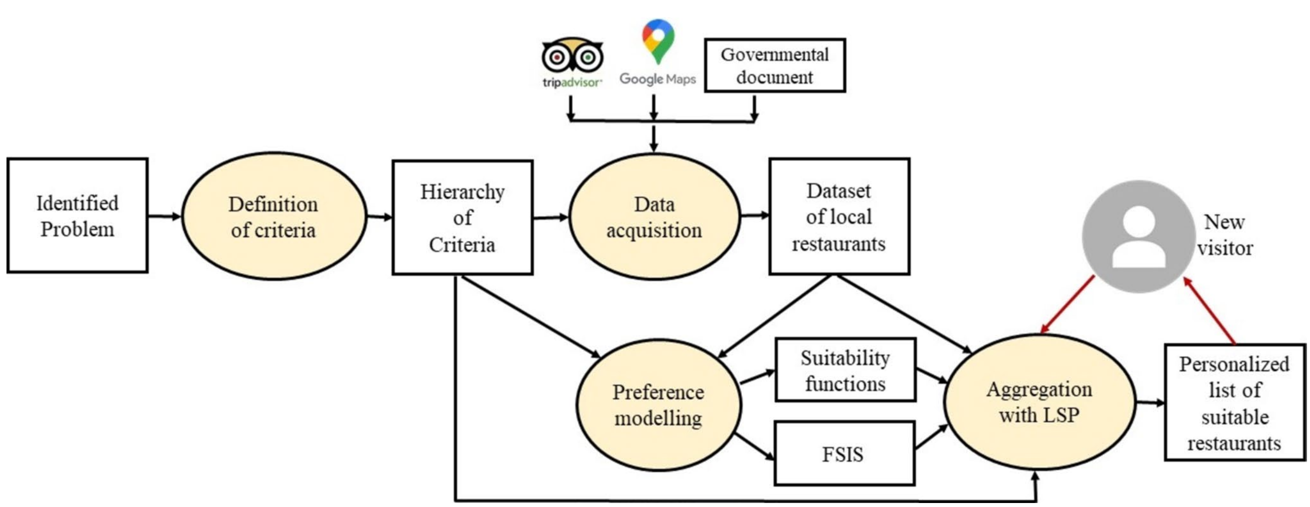


Fig. 1 Diagram of the recommendation system designed

appropriate aggregation operator is crucial for building an appropriate decision support system that represents the user's rationale. For case or restaurant recommendations, we propose the use of a soft computing method called Logic Scoring of Preference method (LSP), which is based on graded conjunction–disjunction aggregation functions [35] that operate on a hierarchical set of criteria. Following LSP standard notation, in the rest of the paper, we will use the term *suitability degree* to refer to the marginal values $v_i(a_j)$ we have on each of the ith criterion of the hierarchy.

The following subsections outline the methodological steps in developing a personalized restaurant recommendation system for emerging destinations using the LSP method. These steps include the identification of relevant criteria and their organization in a hierarchy, acquisition of data from local restaurants, modeling of the user's preferences by means of suitability degrees, and selection of the appropriate weights and aggregation operators in each of the nodes of the hierarchy.

2.1 Identification of Criteria

To identify the criteria and attributes, it is necessary to validate them with experts familiar with the application context, to ensure that the variables are pertinent. During the consultation process with experts, they were asked specific questions related to variables linked to geolocation, aspects of the services, and other distinctive characteristics of the restaurants [42]. Experts have identified five important dimensions to consider: food specialties, services, location, category, and customer score (see Fig. 1). Food specialties may consist of a list of concrete meals or more general types of foods (e.g., pizza, ice cream, burger, and Caribbean food). Regarding relevant services that may be provided by restaurants, the expert's analysis determined that the services to be considered are the acceptance of credit cards for payment, home delivery availability, and meals for vegetarians. Geolocation can be easily determined as the distance to specific relevant points of interest (POI) in the city. This group of criteria may include, for example, distance to beach (in the case of coastal destinations) or distance to the nearest police station (if security aspects are important to be considered in the destination). The number of POIs may differ among cities. Next, the restaurant category can be represented by the average cost of a meal, which permits the user to distinguish luxurious restaurants from cheap ones, such as fast foods. Finally, when possible, it is useful to include the overall restaurant score on web platforms such as TripAdvisor.

Figure 2 shows a list of criteria included in the recommender system and its hierarchical organization. We present a model with three types of attributes: binary, continuous and categorical. The first type comprises attributes with a binary value (yes/no) that indicates whether the specified property is satisfied. For example, "Acceptance of credit card payment" (121). The second set included numerical attributes that took values on a continuous measurement scale. This is the case of the three attributes related to "Location" (121, 122, 123), measured in meters, "Category" (14) measured in the local currency of the country, and "customer score" (15), given as the average score on a Likert scale (for example, 1–5). Finally, the third set consists of a multi-valued attribute composed of a list of words that represent the restaurant's food specialties (11). It should be noted that each restaurant can have several specialties, and we defined the first type of food assigned to a restaurant as its main specialty.

1 RESTAURANT SUITABILITY
11 Food specialties [list of food names]
12 Services
121 Acceptance of credit card payment [Y/N]
122 Availability of delivery service [Y/N]
113 Availability of vegetarians' food [Y/N]
13 Location
131 Distance to POI_1 [Meters]
132 Distance to POI_2 [Meters]
13n Distance to POI_n [Meters]
14 Category [currency units]
15 Customer score [Likert scale]

Fig. 2 Recommender criteria tree

2.2 Data Acquisition

The process of data acquisition for building a restaurant recommendation system in emerging destinations faces several challenges, primarily because of the lack of adequate data [8, 43]. This is a major obstacle in the deployment of smart systems in these areas. Although the amount of tourism data is increasing through social networks and tourism portals, many emerging destinations still do not have the data necessary to develop effective recommendation systems. This limitation is more pronounced in lesser-known destinations or less popular tourist attractions, where less data is likely to be available.

While many restaurants do not have a presence on specific websites or social networks such as Facebook, most of these establishments are listed on the global platform TripAdvisor. In this regard, the proposed model considers the criteria that can be retrieved from the TripAdvisor portal. Web scrapping tools can be used to retrieve data values corresponding to the following criteria: cuisine (11), restaurant category (14), and average customer score (15). The availability of the services included in the model (12) can be also obtained from TripAdvisor by consulting the section "Details" in the website (see Fig. 3).

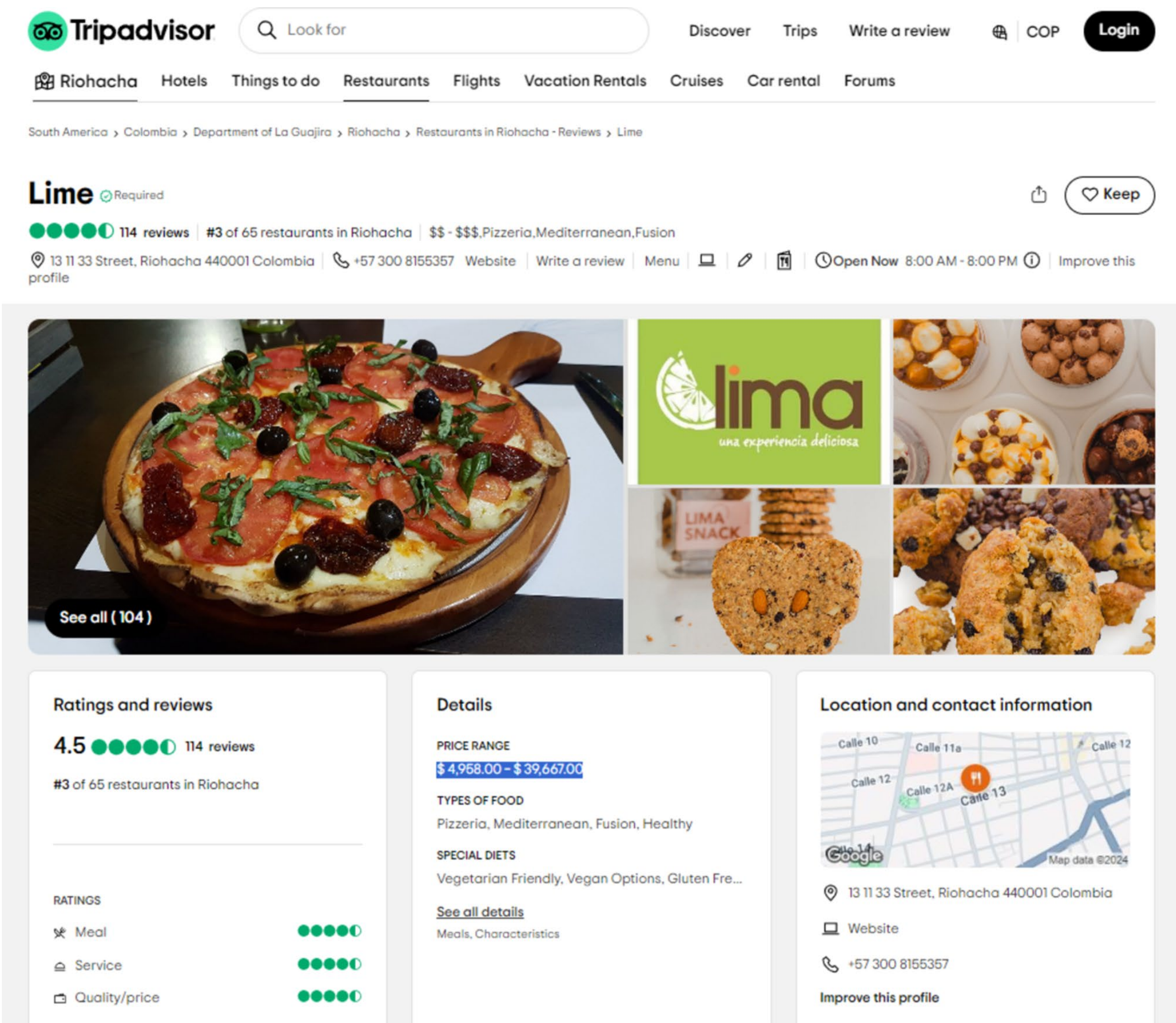


Fig. 3 Information available about the restaurant on TripAdvisor

To calculate the distances between users and restaurants, as well as different points of interest, Google Maps can be used to geolocate both points of interest and restaurants. Finally, to ensure that the listed restaurants are verified businesses and not fraudulent, data provided by governmental organizations with records of restaurant establishments may be consulted.

2.3 Preference Modeling in Uni-valued Criteria

The suitability score denotes the degree of satisfaction of the user requirements with respect to a certain criterion, using a fuzzy membership function. These suitability degrees calculate the strength of the user's preference satisfaction with respect to the input value scale. We can store a different degree of suitability for each user in the recommender system, as their preferences may be unique. However, it is not reasonable to ask travelers who search for a restaurant to spend much time defining the personalized suitability degree for all numerical criteria of the proposed model: location (distance to several POI), category, and customer's score.

To facilitate automatic personalization of the system to the user's expectations with low effort, we designed a small set of predefined suitability degrees for continuous attributes. The user selects the option that represents their preferences. There are three options for the distance criterion (near, medium, far), three for the category criterion (economic, average, expensive), and two for the customer's score (excellent, very good).

This suitability degree must be personalized for each destination, as the range of distances or categories may be different from one place to another. For example, Riohacha (Colombia) has a maximum distance of 7 km, while in another emerging destination, such as Baku (Azerbaijan), it is 20 km. Figure 4 shows the three suitability degrees for distances, measured in kilometers. In the case of near, the user is satisfied (score greater than 80%) when the distance is less than 1 km. The acceptance level falls below 50% when the distance is larger than 4.5 km. For the medium, the user is satisfied with distances between 2 and 35 km. If the user selects the Far option, then high satisfaction is obtained with distances above 6 km, while the user is not accepting distances below 2.5 km.

Figure 5 shows the three suitability degree functions for the category criteria (based on the price of the restaurant given in COP, Colombian pesos). In the case of economy, the user is satisfied (score larger than 80%) when the category is below 40,000 COP. If the user chooses the expensive option, high satisfaction is found with costs above 80,000 COP, while no categories with costs below 50,000 COP are acceptable. In the medium-cost category, the user is satisfied with costs of between 45,000 and 65,000. These options permit the user to indicate whether he/she is searching for a luxurious restaurant for a special occasion, or if he/she needs the cheapest option, even if it may be a low category place, or an intermediate situation between these two extreme ones.

Similarly, a suitability degree can be established for the score that users have previously assigned to the restaurant (see Fig. 6). We considered a 1–5 scale as given in the TripAdvisor platform. We have been defined three options: Excellent, Very Good and "I don't care". Figure 6 shows that, in the case of "Excellent", the user is satisfied when the restaurant has a score between 4.5 and 5.0. If the user chooses the "Very good" option, he/she will be satisfied with a customer score between 4.0 and 5.0, which is less strict than the previous one. Additionally, and only in this attribute, the option "I don't care" is included. This indicates that any restaurant score is suitable for a user. In this case, the model assigns a suitability score of 1 to any restaurant, regardless of its score, because all the scores are satisfactory for the user.

2.4 Preference Modeling for the Multi-valued Criterion Food: Food Specialty Interest Score

Evaluation of multi-valued categorical attributes is not very common, and it usually requires specific models that consider the semantics of the terms and the purpose of their

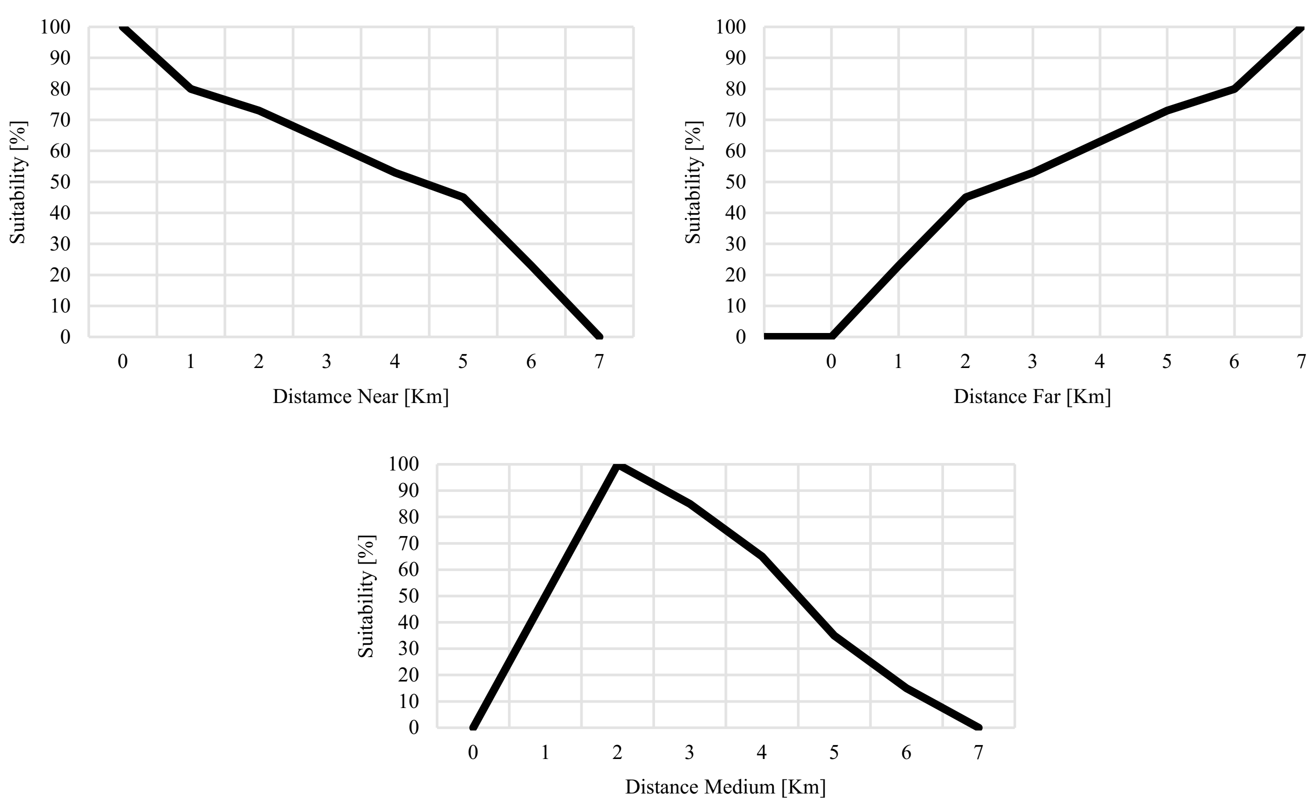


Fig. 4 Suitability degree of the Location criteria for near, far, and medium options

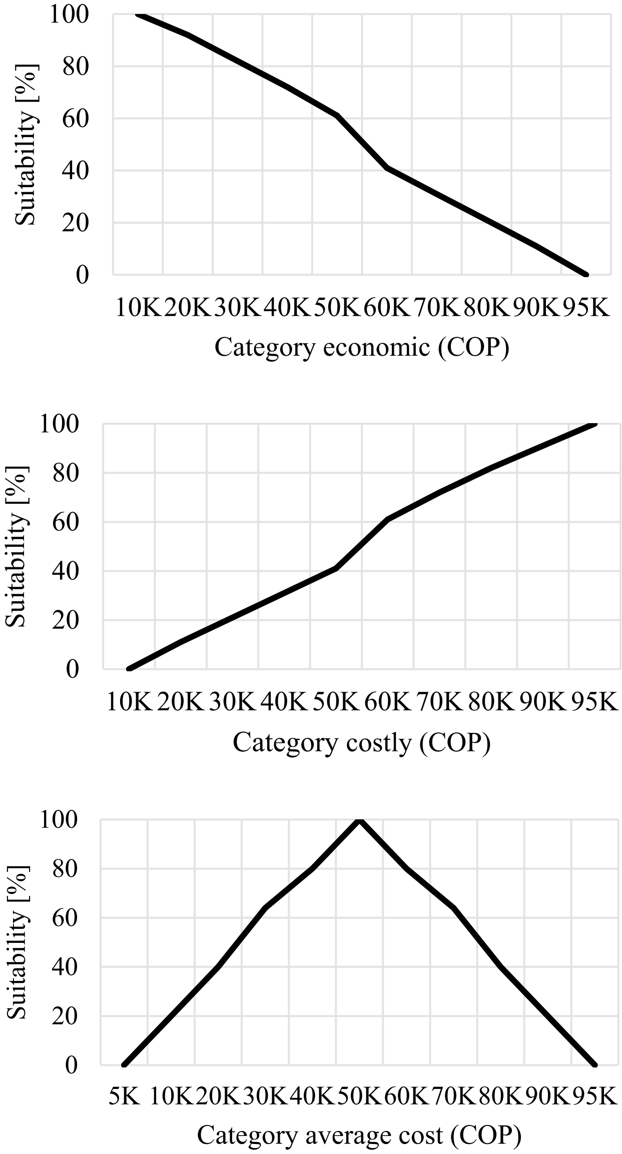


Fig. 5 Suitability degree of the category (economic, costly, and average)

selection [44]. In this paper, we define a new suitability degree called Food Specialty Interest Score (FSIS). The FSIS is a multi-valued indicator that considers the user's interest in different types of food and the types of food offered by a restaurant. After an analysis of restaurants in Riohacha, 25 types of food were identified, some of which were more specific than others. We also observed that the number of different food specialties in a restaurant ranged from 1 to 6. The first type of food is usually the most representative specialty of restaurants.

To calculate the Food Specialty Interest Score (FSIS), first, the user u selects a subset of all the available food specialties. We have then the set $\text{UserSelection}(u) = \{s_1, s_2, \ldots, s_p\}$. And let us define the set of food specialties for restaurant a_j as $\text{FoodSpecialities}(a_j) = \{f_1, f_2, \ldots, f_q\}$.

The FSIS value is obtained applying a weighted power mean with $w_i = 1/q$, as indicated in Eq. 1:

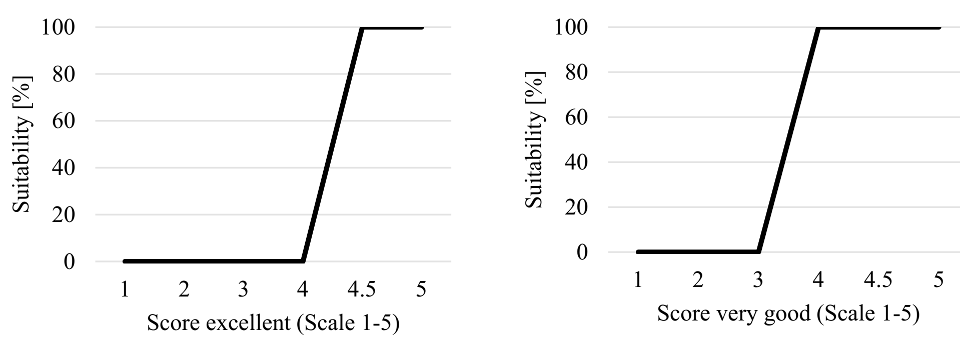
$$\text{FSIS}(a_j) = \sqrt[r]{\sum_{i=1}^{q} \left(\frac{1}{q} m_i^r\right)} \quad (1)$$

The matching between the user selection and the ith food specialty of restaurant a_j is measured as $m_i = \begin{cases} \varphi_i, & \text{if } f_i \in \text{UserSelection}(u) \\ 0, & \text{if } f_i \notin \text{UserSelection}(u) \end{cases}$, which uses a position-based suitability score defined as: $\varphi_i = \begin{cases} 0.5, & \textit{if} \quad i = 1 \\ 0.25, & \textit{if} \quad i = 2 \\ \frac{0.25}{q-2}, & \textit{if} \quad i > 2 \end{cases}$.

In case of restaurants with a single specialty ($q = 1$), $\text{FSIS}(a_j) = 1$ if the user selected that food type, and $\text{FSIS}(a_j) = 0$, otherwise.

The value of r in Eq. 4 is determined by the level of *orness* to be used in the aggregation of the food scores, making possible a modeling of a soft disjunctive aggregation

Fig. 6 Suitability degree of customer score for excellent and very good options



[35]. A value of *orness* of 0.65 is proposed for this attribute because a restaurant may not fulfill all the selected food types of a user at the same time for two reasons, on the one hand, because a user may have selected quite distinct foods (e.g., pizza and sushi), and on the other hand, because a restaurant may serve a large variety of foods, being only a subset of them suitable for the user (e.g., a restaurant serves Italian, Seafood, Fast food, and Sushi, while the user just selected Sushi).

2.5 LSP-Based Restaurant Recommender System Architecture

Logic scoring of preference (LSP) is a MCDA method for the evaluation and aggregation of the suitability degree using a logic-based aggregation procedure. The LSP is based on the use of graded logic aggregation operators on a hierarchically structured set of criteria [35, 45].

Each intermediate node in a hierarchy of criteria corresponds to a high-level criterion with a relevant meaning for the decision-maker, which has a unique interpretation, specific semantic identity, and concrete importance to the interpretability and explainability of the decision [46]. Each node applies a Graded Conjunction/Disjunction (GCD) aggregation operator [47], which is selected from continuous preference logic (CPL), ranging from simultaneity (andness) to substitutability (orness). In [47], several sets of GCD operators were characterized. In this work, we have considered the use of a 17-level scale, composed by the following operators: C, C++, C+, C+−, CA, C−+, C−, C–, A, D–, D−, D−+, DA, D+−, D+, D++, D. Within this set, three base aggregators stand out: conjunction (C) when andness is 1, weighted arithmetic mean (A) when andness = orness = 0.5 and disjunction (D) when andness is 0 and orness is 1.

One of the simplest and most effective implementations of LSP is through the calculation of the weighted power mean (WPM), shown in Eq. (2). It involves the use of a parameter r that adjusts the polarity of the aggregation. The value of r is determined based on the andness/orness value and number of entries in the evaluation process. In addition, WPM allows for assigning an importance degree representing the importance of each of the inputs involved in the evaluation.

2.5.1 Implementation of the Graded Logic Operators

There are several functions that can be used to implement a GCD aggregator [35]. For simplicity, in this paper, we use the following weighted power mean (WPM) function, Eq. 2, that is applied to a tuple of suitability degrees (X):

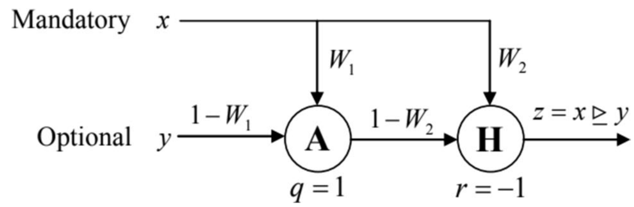


Fig. 7 Conjunctive partial absorption (CPA)

$$\mathrm{WPM}(X) = \sqrt[r]{\sum_{i=1}^{n}(w_i x_i^r)}, x_i \in [0,1], 0 < w_i < 1, \quad \sum_{i=1}^{n} w_i = 1, -\infty \le r \le +\infty \tag{2}$$

If $r \le 0$, WPM is a hard conjunctive aggregator supporting the annihilator 0. In the range $0 < r < 1$, WPM is a soft conjunctive aggregator (positive values of inputs are desired, but not mandatory). For $r = 1$, we have the logic neutrality (the arithmetic mean), and for $r > 1$, we have a soft disjunction.

On the other hand, the LSP method proposes some compound asymmetric aggregators to represent situations with mandatory and optional criteria (conjunctive partial absorption, CPA), or with sufficient and desired criteria (disjunctive partial absorption, DPA). These asymmetric aggregators are useful tools to address various situations and preferences in the multi-criteria decision process [48, 49]. For this reason, we only introduce below the CPA.

Our hypothesis is that the incorporation of these diverse logic-based operators in the model of recommendation may bring greater flexibility and quality when evaluating a restaurant from the point of view of the user's preferences.

2.5.2 Conjunctive Asymmetric Partial Absorption

Conjunctive Partial Absorption is an idempotent logically asymmetric conjunctive aggregator CPA: $I^2 \rightarrow I$ that has heterogeneous annihilators: one argument, called the mandatory input (x), has the annihilator 0, and the other argument, called the optional input (y), does not have the annihilator 0. CPA aggregator is symbolically denoted as $z = x \trianglerighteq y$. So, $0 \trianglerighteq y = 0$, $0 \le y \le 1$ and $0 < x \trianglerighteq 0 < x$, $0 < x \le 1$. Therefore, when the mandatory input requirement is not satisfied, the entire criterion is considered unsatisfied (corresponding to 0 suitability degree). However, the same does not hold true for the optional input as the compound criterion can still be partially satisfied even if the optional input's requirement is not fulfilled. The optional criterion has the ability of giving a reward or a penalization with respect to the suitability degree of the mandatory criterion.

The aggregation of the mandatory input x and a desired input y can be done using a combination of two different operators as defined in LSP methodology [48]. For the restaurant recommender system, we propose the use of the AG operation as depicted in Fig. 7. In the first step, the two inputs are aggregated with an arithmetic average (A) using a weight W_1, and in the second step, the Harmonic mean (H) is applied with weight W_2. This aggregation can be implemented using Eq. (3). The parameters W_1 and W_2 are determined by the desired values of penalty and reward in the asymmetric aggregation. The concepts of penalty and reward are fundamental in CPA.

$$AH(x, y) = \left[W_2 x^{-1} + (1 - W_2)\left(W_1 x + (1 - W_1)y\right)^{-1}\right]^{-1} \quad (3)$$

When $y < x$, we can say that the provided value of x is penalized by the insufficient satisfaction of y. That yields the following definitions of the local penalty:

$P_{\mathrm{CPA}}\ (x, y) = x - x \trianglerighteq y$.

If $y > x$, then both $x \trianglerighteq y > x$ and $x \,\overline{\triangleright}\, y > x$. So, we can say that the provided value of x is rewarded by the abundant satisfaction of y. This yields the following definitions of the local reward:

$R_{\mathrm{CPA}}\ (x, y) = x \trianglerighteq y - x$.

When x and y are binary suitability values, $x \in \{0,1\}$, $y \in \{0,1\}$, then the CPA operator has the following properties:

$$\mathrm{CPA}(0, y) = 0, \text{ and } \mathrm{CPA}(1,1) = 1.$$

And for the case of AH, the following properties also hold:

$$AH(1,0) = \left[W_2 + (1 - W_2)/W_1\right]^{-1} = 1 - P_{CPA}.$$

If we use the natural harmonic mean, then $W_2 = 1/2$, and the other weight is$W_1 = (1 - P_{\mathrm{CPA}})/(1 + P_{\mathrm{CPA}})$. That works for any desired value of penalty. E.g., if we need $P_{\mathrm{CPA}} = 1/3$, then we should use $W_1 = 1/2$.

2.5.3 Aggregation Operators in the Restaurant Recommender System

Figure 8 shows the architecture of the recommendation model for calculating the overall suitability score for restaurants in emerging tourist destinations. It is organized hierarchically following the tree presented in Fig. 2.

In the first level, there are five attributes from restaurant customers: food specialty, services, location, category, and web score. The relative importance degree is determined by the user according to their preferences. The suitability of the user for food specialty was calculated using the FSIS indicator.

Within the Services group, suitability is obtained from the aggregation of binary inputs corresponding to the possible services of interest of the user. In Fig. 8, we have selected three common attributes, but others can be included: card payment, delivery service, and vegetarian-friendly. These inputs are merged by the asymmetric aggregator or partial absorption function, where the user can define which of these inputs is mandatory and which are optional. The asymmetric CPA aggregator using harmonic mean AH is proposed. The mandatory suitability degree is obtained using the conjunction operator C+, and the optional inputs are averaged (A). From experimental analysis, the parameters of CPA have been fixed to $W_1 = W_2 = 1/2$, having that the resulting penalty degree is $P_{\mathrm{CPA}} = 1/3$. The user must

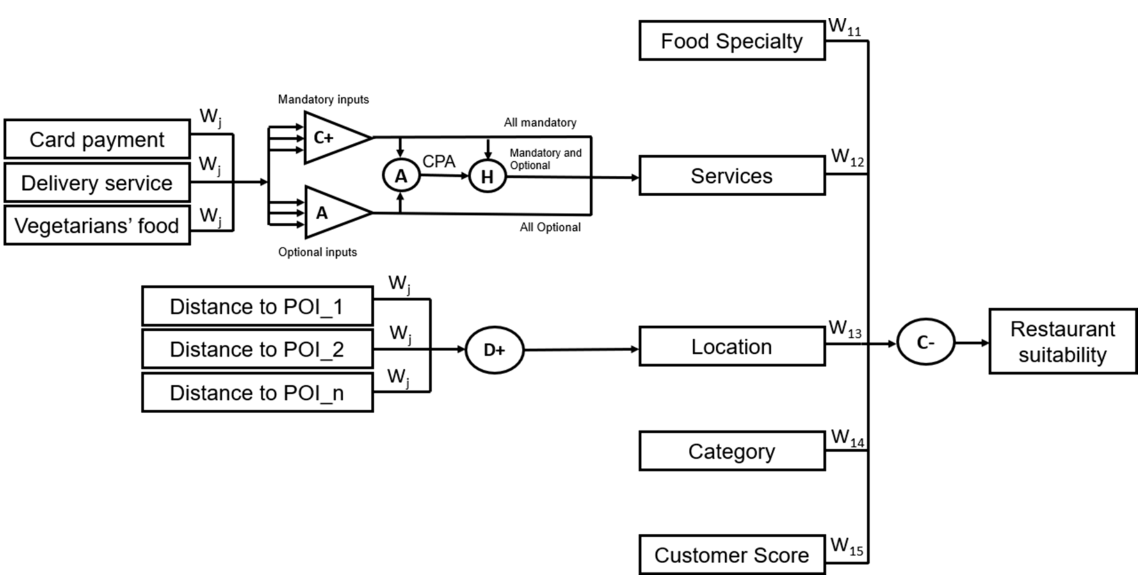


Fig. 8 LSP-based recommender system model

indicate the relevance of each of the services according to his/her requirements. Specifically, the user inputs weights for criteria, such as food specialty, services, location, category, and customer score. These weights reflect the user's personal preferences and priorities when selecting a restaurant. Regarding the weights of the Services group of criteria, the designer must determine an overall weight w_M for the mandatory criteria and the overall weight w_O for the optional ones. When the user selects mandatory and optional criteria, the system divides the overall weight by the number of criteria of each type. Thus, having m mandatory criteria and n optional ones, the importance of each mandatory criterion isw_M/m, whereas the importance of each optional criterion corresponds tow_M/n.

Regarding the location criterion, for attributes such as the distance to points of interest (distance to POI_1, distance to POI_2, and distance to POI_n), the weight is the same for all criteria and is defined based on the number of points of interest, ensuring that the total sum of the weights is 1.0. The composed location attribute is obtained from a disjunctive aggregation of different inputs, as example, denoted as POI_1, POI_2, and POI_n. The selected operator is aggregator D+ because the geographical distribution of these points of interest along the city may make it difficult to satisfy them simultaneously. The same weights were proposed for different distances to the POI to reduce the number of parameters introduced by the user. However, the model can easily handle user-defined weights if we want to allow them to indicate which POI is more relevant to the decision.

Finally, the logical aggregator C− is used to calculate the overall restaurant suitability, which serves as a support for making recommendations to tourists through the ranking of the best-rated restaurants. This operator was selected to model a certain degree of simultaneity in the satisfaction of different aggregated attributes. From the different levels of conjunction, C− was selected from empirical analysis. Table 3 lists the LSP aggregation operators used in the recommendation model.

3 A Restaurants Recommender for Riohacha

The proposed recommender system model was used to build a tool for the District of Riohacha, in Colombia. Figure 9 shows the location of this district, which is located

Table 3 Logical operators used in the model

Type of polarization	Level of polarization	Symbol	Orness	Andness	Attribute
Conjunctive	Strong	C+	0.125	0.875	Service—mandatory
Average	Neutral	A	0.5	0.5	Service—optional
Disjunctive	Strong	D+	0.87	0.12	Location
Conjunctive	Medium	C−	0.37	0.62	Score global

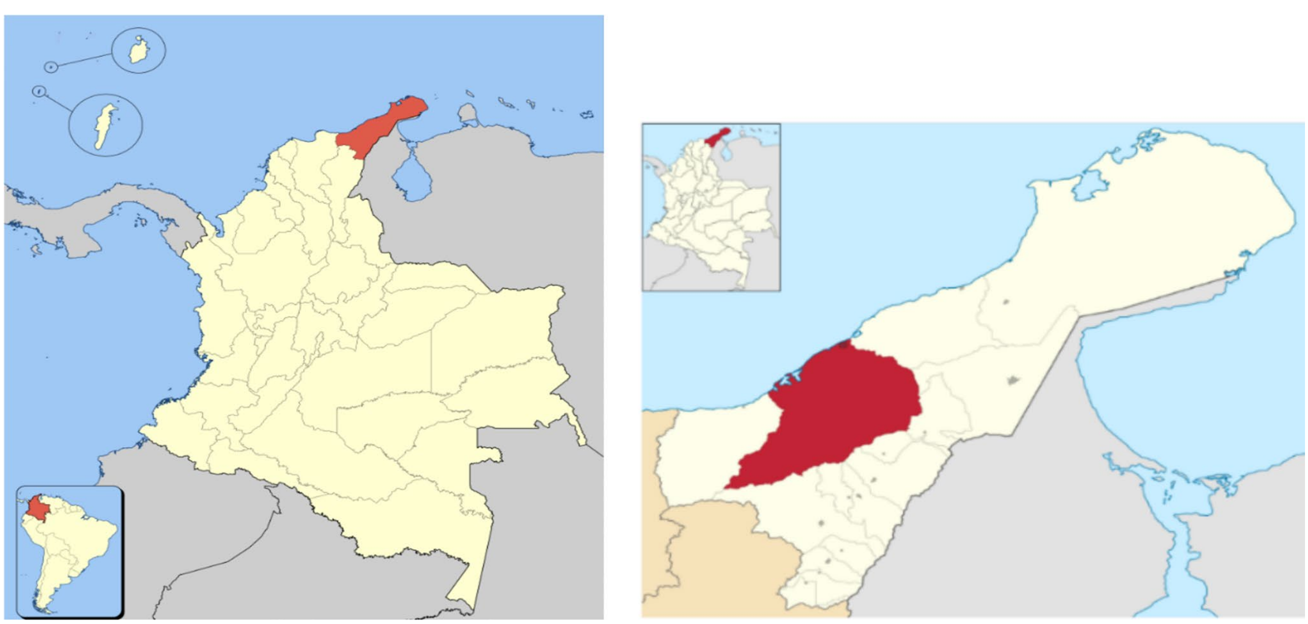


Fig. 9 Location of Riohacha. Source: wikipedia.org

in northern South America. Riohacha is the capital of the Department of La Guajira, an area of Colombia that wants to promote tourism to increase its wealth and social opportunities. Riohacha received the category of *Special, Tourist, and Cultural Districts* under Law 1766 on 24 July 2015.

The Special, Tourist, and Cultural District of Riohacha is projected to position itself as a competitive, attractive, and safe tourist destination at the national and international levels, increasing the current levels of visitors. According to the Riohacha District Development Plan 2020–2023 "Riohacha Cambia la Historia" [50], the tourism main focuses are: (1) cultural tourism; (2) nature tourism and (3) sun and beach tourism. For all these types of tourism, it is necessary to improve gastronomy services, not only because eating is a basic need for any tourist, but also because of the characteristics and diversity of Guajira's gastronomy for those who visit the district.

1 RESTAURANT SUITABILITY
11 Food specialties [list of food names]
12 Services
121 Acceptance of credit card payment [Y/N]
122 Availability of delivery service [Y/N]
113 Availability of vegetarians' food [Y/N]
13 Location
131 Distance to Beach [Meters]
132 Distance to City Historical area [Meters]
133 Distance to Pier and tourist police [Meters]
14 Category [COP]
15 Customer score [Scale 1-5]

Fig. 10 Criteria tree for the recommender system in Riohacha

3.1 Hierarchy of Criteria for Riohacha

Following the proposed criteria structure, an instantiation for the case of the city of Riohacha was made with the help of local stakeholders. Figure 10 shows the list of criteria included in the recommender system and their hierarchical organization. The selected criteria for Services are 3: 'Acceptance of credit card payment', 'Availability of delivery service', 'Availability of vegetarians' food'. In the case of Location, three relevant places in Riohacha have been selected: POI_1 = Beach, POI_2 = City Historical Zone, and POI_3 = Pier&Police. The beach and the historical zone are the areas that concentrate more touristic activities, such as monuments, handicrafts stores, churches, among others. The third point of interest relates to the safety of tourists. The police office is located at the pier, where in addition you can find some touristic attractions like the Malecón, Pier or the cathedral.

Figure 11 presents the LSP-based recommender system model for restaurants tailored specifically for the emerging tourist destinations of Riohacha. These criteria were adapted to consider the unique characteristics of the destination.

3.2 Data Values of the Riohacha Restaurants

The study presented in this paper was conducted with a set of 18 restaurants in the District of Riohacha, from those with data available in TripAdvisor. These selected restaurants belong to the list of verified companies registered in the Chamber of Commerce of La Guajira, an institution that maintains and updates the commercial registers of economic service providers.

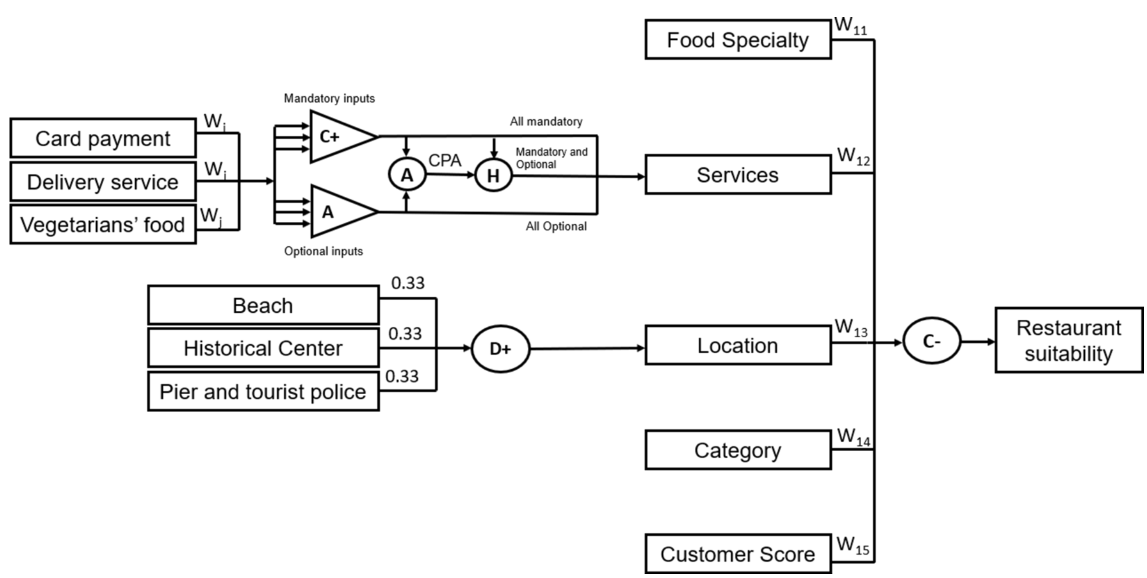


Fig. 11 LSP-based recommender system model for restaurants in Riohacha (Model 1)

Table 4 Data values of the Riohacha restaurants

N	Restaurant	Specialties	Category	Score
1	Al Arz Delicias Árabes	Lebanese, Middle Eastern	40,000	4.5
2	Casa Vieja Café & Bar	Coffee	60,000	3.5
3	Hope Burgers	Fast food, Pub	11,650	4.5
4	I Wanna	Coffee, South American, Colombian	20,000	5
5	La Fermata Pizza Bistro	Italian, Pizzeria	75,800	4.5
6	La Heladería	Coffee, Fast food	60,000	4
7	La Jaus by La Trece	Caribbean, Mediterranean, Pizzeria, Spanish, Fusion, South American, South American	48,544	5
8	La Morena	South American	50,000	4
9	La Tinaja	Seafood, Colombian, South American	180,000	4
10	La Trece Bistró	Gastropub, American, Caribbean, Pub Bar	26,000	5
11	Lima	Latin, Mediterranean, Colombian, Fusion, South American	40,000	4.5
12	Pichigüel Café	Latin, Colombian, Spanish, South American	40,000	4
13	Picnic Rioh	Italian, Seafood, Fast food, Sushi, Gastropub	50,000	5
14	Quile Parrilla	Grill, Argentina, South American, Colombian	80,000	4
15	Restaurant La Casa del Marisco	Caribbean, Latin, Seafood, Soups, Colombian, Spanish	160,000	4
16	Restaurant Mantequilla	Colombian, Fusion, South American	120,000	4.5
17	Restaurant Yotojoro	Caribbean, Seafood, Colombian International	300,000	4.5
18	Zeroa	Caribbean, Fusion, Healthy	60,000	4.5

Table 4 shows the data table, except for location. The restaurant category is measured by the price of a meal given in the Colombian pesos COP. The customer's score is the average rating value, from 1 to 5, published on the TripAdvisor platform.

3.3 Experimentation with Different User Profiles

Eight profiles representing people from different parts of the world were created to validate and evaluate the proposed model. It is important to note that these profiles do not correspond to real users but serve as prototypes for the representation of diversity.

Table 5 shows the weights defined by the users for each of the categories of the proposed model, among which are: food specialty, service, location, category, and score. Table 5 shows the degrees of importance defined for each first-level criterion. The sum of these weights is equal to 1.0 in each profile. Some profiles assign 0 to one of the attributes to indicate that this feature must not be considered for the recommendation.

Table 6 displays the preferences of the user profiles for each elementary criterion in our model. The number of mandatory attributes changes among the profiles. We also have some people with a longer list of suitable foods, while others are looking for only one or two types of meals. Rest of criteria also model different kinds of searches by different users (with different selection of restaurant category, or location).

3.4 Comparison Study

A comparison with other recommendation techniques is not possible due to the lack of data to build other types of systems, such as collaborative ones. In order to evaluate different components of the proposed recommendation model, we have made an ablation study. We implemented two simplified variants that did not include parts of the

Table 5 Weights of main criteria used in experiment for each profile

Criteria	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Profile 6	Profile 7	Profile 8
Food specialty	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.4
Service	0.2	0.1	0.2	0.2	0.3	0.2	0.3	0
Location	0.1	0.2	0.3	0.2	0.2	0.2	0	0.3
Category	0.2	0.3	0.2	0.3	0.2	0.1	0.2	0.3
Score	0.3	0.2	0	0	0	0.2	0.2	0

Table 6 Preferences of the 8 user profiles in the experimentation (M: Mandatory; O: optional)

Criteria	Sub-criteria	Prof1	Prof2	Prof3	Prof4	Prof5	Prof6	Prof7	Prof8
Specialty	Food specialty	Latin, Spanish, Colombian, grill	American, Italian, Pizza. Gastropub	Mediterranean, Caribbean, Grill, Colombian, Lebanese	Italian, Pizzeria, Fusion, Coffee	South American, Fast food	Argentinian, Spanish, Fast food, Caribbean	Colombian	Gastropub, Lebanese
Service	Card payment	M	M	M	M	O	M	O	O
	Delivery service	O	O	M	M	O	M	O	O
	Suitable vegetarian	O	O	O	M	O	O	O	O
Location	Beach	Far	Near	Medium	Near	Medium	Medium	Medium	Medium
	Historical Center	Near	Near	Far	Far	Near	Medium	Medium	Near
	Pier/tourist police	Near	Near	Near	Near	Near	Near	Medium	Near
Category	Category	Expensive	Average	Expensive	Expensive	Average Cost	Average	Average	Average
Score	Customer score	Excellent	I don't care	Excellent	I don't care	I don't care	I don't care	Very good	I don't care

full architecture. For all models, we use the FSIS index, which calculates user interest based on the types of meals offered in a restaurant.

- Model 2 uses the same hierarchy, but the average operator is used for aggregation both for services, location, and the overall suitability score. This is illustrated in Fig. 12. Due to the lack of asymmetric operators in this model, an adaptation is made to calculate the weights of the attributes of the service criterion, denoted as w_i. We assign equal weights only to those attributes that the user declares as mandatory. For optional ones, $w_i = 0$.
- Model 3 does not have a hierarchy of criteria, but all attributes are aggregated at the same level. The average was used for aggregation, as shown in Fig. 13. This can be considered a base model which compares the other versions. This model is similar to the usual content-based recommender systems in the literature and is based on a direct comparison of the features of the user and items. In this model, we distribute the weight given to attributes 12 (service) and 13 (location) into their descendants. In

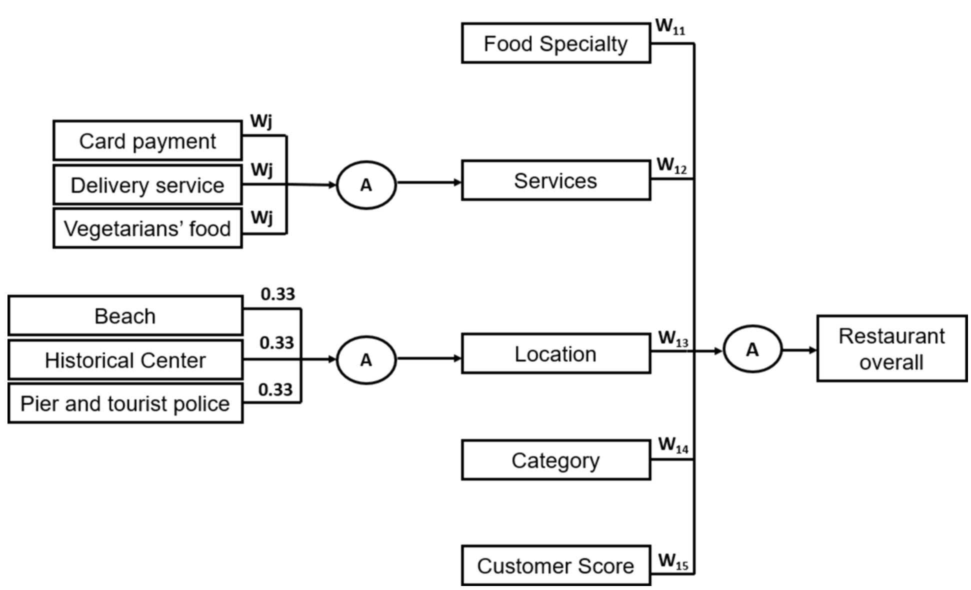


Fig. 12 Model 2: with hierarchy and the use of averaging

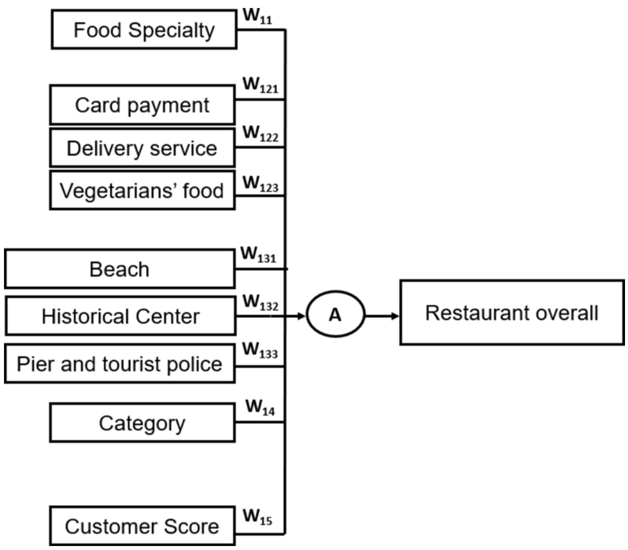


Fig. 13 Model 3: model without hierarchies and average calculation

the case of the service attributes, similarly to Model 2, equal weights are assigned only to those attributes that the user has declared as mandatory.

4 Validation with Experts

After implementing the three models presented in the previous section, we conducted an experiment with each of the users listed in Table 6. Once we obtained the results for each model, we selected the three best B and three worst restaurants W. The best restaurants had to meet the criteria of having scores the highest final scores and satisfy the condition OverallSuitability > = 0.75. For the worst restaurants, they should have the lowest scores and satisfy the condition OverallSuitability < = 0.4. For each model x and user profile, a list of six restaurants was built with the best and worst: $[R_{1x}, R_{2x}, R_{3x}, R_{4x}, R_{5x}, R_{6x}]$.

Three knowledgeable experts from Riohacha were consulted to validate the restaurants recommended by of the three models. The experts were provided an evaluation form that included the best and worst restaurants. They were also given the user preferences detailed in Table 6. In this form, the evaluators had to assign a correctness score to each restaurant using the following evaluation scale: 0 to indicate that the recommendation was not correct, 1 to indicate that the recommendation was correct and acceptable, and 2 to indicate that the recommendation was correct as well as a good option for the user.

After obtaining the evaluation points given by the 3 experts, for each restaurant R_i, the accumulated total number of points has been calculated, denoted $\text{expertsValue}(R_i)$. We can then define the following indicators:

Table 7 Results of the recall of the three models

	Best restaurants	Worst restaurants
Recall model 1	1	1
Recall model 2	0.667	1
Recall model 3	0.428	1

- Hit: if $R_i \in B$ and $\text{expertsValue}(R_i) \geq 5$, or if $R_i \in W$ and $\text{expertsValue}(R_i) \leq 2$.
- Failure: if $R_i \in B$ and $\text{expertsValue}(R_i) \leq 2$ or if $R_i \in W$ and $\text{expertsValue}(R_i) \geq 5$.

Being $Y = \{B, W\}$, we define $TP(Y) = \sum_{i \in Y} \text{hit}_i$ and $FN(Y) = \sum_{i \in Y} \text{failure}_i$. Then, we can calculate the Recall measure for the subset B and W as, Eq. 4:

$$\text{Recall}(Y) = \frac{\text{TP}(Y)}{\text{TP}(Y) + \text{FN}(Y)} \tag{4}$$

Table 7 shows the recall results for the three models evaluated. Results show that the proposed model using LSP exhibits a performance score of 1, achieving optimal recommendation both for the best and worst restaurants and all the user profiles. Figure 14 illustrated the number of hits (TP + FN) and failures (FP + TN) for each model for the restaurants in $B = \{\text{R1,R2,R3}\}$ and the ones in $W = \{\text{R4,R5,R6}\}$. The results reveal that the proposed model in this paper achieves the highest performance providing good recommendations.

Table 7 shows that Model 2 is accurate for top-rated establishments and exhibits some errors, leading to a recall rate of 0.66. Conversely, Model 3, although accurate for some of the best restaurants, demonstrated a lower error rate, resulting in a recall rate of 0.428. We observe that Model 1 does not exhibit any failures. In Model 1, for Restaurants 1 and 3, some of the total scores obtained from the expert evaluations ranged between 3 and 4, indicating that none of these scores met the criteria necessary to be classified as a failure (see Fig. 14).

5 Analysis and Discussion of Some User Profiles

In addition to the general study of the quality of results presented in the previous section, we analyze three of the profiles in detail. They represent very different user's

Fig. 14 Results of the evaluation of the models

requirements. The restaurants in the best and worst positions will be presented, and their correspondence with the preferences introduced in the recommender will be discussed. Results of the three models (Models 1, 2, and 3) will be compared. For Model 1 and Model 2, the same weights are taken as given in Table 6. For Model 3, the weights are distributed as follows: criteria 11, 14 and 15 receive the same weighting as assigned by the user, while the weights of criteria 12 and 13 are divided between their respective attributes. Additionally, Models 2 and 3 perform an initial filtering stage to remove all restaurants that do not satisfy the mandatory requirements.

5.1 Profile Number 1

This profile represents a Spanish tourist, who establishes the following weights: food specialty (0.2), service (0.2), location (0.1), category (0.2), customer rating (0.3). Within the food specialty, he/she prefers Latin, Spanish, Colombian and Grill. He/she would like the restaurant to: accept credit cards (mandatory), Have a delivery service (optional), Be suitable for vegetarians (optional). In terms of location, the user is looking for the restaurant to be: historic center (far), beach (near) and pier/tourist police (near). He/she plans a special gastronomic experience, so he selects an Expensive option for category criterion, as well as an excellent value in customer rating. Table 8 shows result of this profile for Model 1. The columns display the suitability values obtained for the first-level attributes (see identifiers in Fig. 2), and the overall suitability is named with the corresponding aggregation operator C−.

Restaurant "Pichigüel Cafe" is found as the best option with a final score of 0.82. The second option is “Quile Parrilla”, but the final suitability is much lower. On the other hand, it can be observed that the worst restaurants obtain a very low overall suitability because they have a 0 for food specialty. The model correctly understands that the non-suitability of the food offer cannot be compensated for with high values in other criteria.

Model 2 results are given in Table 9 for the same user profile. In this case, the model applies the weighted arithmetic average to all levels of the hierarchy of criteria. The two best restaurants are again "Pichigüel Cafe" and "Quile Parrilla", which now obtain very close overall scores. Restaurant "Quile Parrilla” compensates its low performance in Location with the other values. The worst restaurants for this user are "Yotojoro" and "Casa Vieja Café & Bar”, with a final score of 0,427. In this case, any restaurant has a score below 0.4, even those having more than one criterion with 0 suitability, due to the compensatory property of average.

Table 10 shows the results of this profile for Model 3, which aggregates directly all the elementary criteria with

Table 8 Model1 suitability scores for the best and worst restaurants in Profile1

Restaurant	11	12	13	14	15	C−
Best options						
Pichigüel Cafe	0.94	1	0.88	0.57	0.8	0.82
Quile Parrilla	0.82	0.87	0.39	0.86	0.8	0.77
Worst options						
La Trece Bistro	0	0.71	0.74	0.37	1	0.11
Casa Vieja Café & Bar	0	0.71	0.38	0.86	0	0

Table 9 Model 2 suitability scores for the best and worst restaurants in Profile 1

Restaurant	11	12	13	14	15	A
Best options						
Pichigüel Cafe	0.94	1	0.62	0.57	0.8	0.81
Quile Parrilla	0.82	1	0.39	0.86	0.8	0.80
Worst options						
Yotojoro	0.53	1	0.3	0	0.9	0.606
Casa Vieja Café & Bar	0	1	0.55	0.86	0	0.427

Table 10 Model 3 suitability scores for the best and worst restaurants in Profile 1

Restaurant	11	121	122	123	131	132	133	14	15	A
Best options										
Pichigüel Cafe	0.94	1	–	–	0.06	0.9	0.91	0.57	0.8	0.80
Quile Parrilla	0.82	1	–	–	0.36	0.4	0.4	0.86	0.8	0.81
Worst options										
La Tinaja	0.53	1	–	–	0.02	0.95	0.98	0	0.8	0.611
Casa Vieja Café & Bar	0	1	–	–	0.06	0.77	0.82	0.86	0	0.427

the average operator, without considering any hierarchical structure. The columns correspond to the overall values obtained for each of the elementary attributes of the tree (see identifiers in Fig. 1).

Among the most outstanding options, we again have "Pichigüel Cafe" and "Quile Parrilla", with a final score of 0.81 and 0.80. The least favorable results are now "La Tinaja" and "Casa Vieja Café & Bar", which have scores of 0.611 and 0,427, respectively. Both restaurants have a non-sufficient performance in the food specialty. They have also low scores in other criteria, like category or customer's ranking. Despite this low performance in many criteria, they still achieve an overall suitability score close to 0.5.

In summary, for this user profile, the two best restaurants are clearly identified by all the models. Model 1 is the unique that is able to give a distinct overall suitability degree to them. In this case, "Quile Parrilla" receives a lower suitability score because of its poor location (low suitability in Location, attribute 13). The other two simpler models are not able to properly represent this weak point of "Quile Parrilla". Regarding the restaurants with lowest suitability, "Casa Vieja Café & Bar" is considered the worst for the three methods. While the second worst position changes depending on the aggregation model.

5.2 Profile Number 4

This profile represents a rich Italian tourist, who is not interested in the ratings given by previous tourists, but he/she focuses on the rest of criteria, mainly searching luxurious restaurants serving Italian meals. The weights are set as follows: food specialty (0.3), Service (0.2), Location (0.2), category (0.3), and customer score (0). Preferences are: in Specialty Food: Italian, Pizzeria, Fusion, and Coffee; in Service: Accepts credit card payment (mandatory), Serves home delivery (mandatory), Suitable for vegetarians (mandatory): in location: beach (near), historical center (far) and pier/ tourist police (near); in category range: expensive. Finally, customer score is not relevant as it has a weight of zero and will not be considered by the model.

Tables 11, 12, and 13 present the results of each of the three models for Italian tourists. It is highlighted that for all three models, the same restaurant is recommended as

Table 11 Model 1 suitability scores for the best and worst restaurants in Profile 4

Restaurant	11	12	13	14	15	1
Best options						
La Fermata Pizza Bistro	0.87	1	0.55	0.92	–	0.83
Zeroa	0.53	1	0.84	0.86	–	0.77
Worst options						
Yotojoro	0	0.26	0.78	0	–	0
La Tinaja	0	0.26	0.94	0	–	0

Table 12 Model2 suitability scores for the best and worst restaurants in Profile4

Restaurant	11	12	13	14	15	A
Best options						
La Fermata Pizza Bistro	0.87	1	0.44	0.92	–	0.82
Casa Vieja Café & Bar	1	0.33	0.62	0.86	–	0.75
Worst options						
La Tinaja	0	0.67	0.66	0	–	0.26
Yotojoro	0	0.67	0.54	0	–	0.24

Table 13 Model3 suitability scores for the best and worst restaurants in Profile4

Restaurant	11	121	122	123	131	132	133	14	15	A
Best options										
La Fermata Pizza Bistro	0.87	1	1	1	0.37	0.6	0.34	0.92	–	0.52
Casa Vieja Café & Bar	1	1	0	0	0.9	0.12	0.82	0.86	–	0.43
Worst options										
La Tinaja	0	1	0	1	0.96	0.03	0.98	0	–	0.19
Yotojoro	0	1	0	1	0.86	0.33	0.42	0	–	0.21

the best option, since it aligns perfectly with the user's specific interests and as a food specialty: Italian, Pizzeria, Fusion, and Coffee. Its unique weak point is the location but it satisfies with very high degree al the rest of criteria. The two worst restaurants are also the same for all the models, with an important difference in the final suitability degree obtained. While they obtain a value of 0 in the proposed Model1, they receive a value close to 0.2 in the other models.

5.3 Profile Number 8

This is a Greek tourist profile, who is not interested in evaluating the services nor the scores given in TripAdvisor by other customers. So, he/she assigns weights to its criteria as follows: food specialty (0.4), service (0), location (0.3), category (0.3), and customer score (0). Preferences are as follows: in specialty food: Gastropub and Lebanese; in location: beach (medium), historical center (near), and pier/tourist police (near); in category range: average cost.

Tables 14, 15, and 16 present the results of each model proposed in this analysis. The results reveal similar choices because the two types of food preferred by this user are not common in Riohacha restaurants. We have a single restaurant “Al Arz Delicias Arabes” serving Lebanese food, and two gastropubs, being “La Trece Bistro” the one with most appropriate location and category. The final suitability degrees obtained using the three models were more similar in this case than in the other profiles. Therefore, when the search made by the user is limited to a few types of food and to a reduced number of criteria (with weights equal to 0), then the performance of the three models is similar as the advantage of the logical hierarchical aggregation structure proposed in Model1 has less relevance in the decision.

5.4 Discussion of the Profiles Study

After observing the best and worst options obtained using the three studied aggregation models, we can see that the recommended restaurants are not always the same. Even for the same restaurants, it is especially relevant to note that the overall suitability scores are generally quite different. The proposed architecture in Model 1 is the one that better distinguishes the best restaurant in each profile. In situations with a significantly reduced number of food preferences and/or elimination of some criteria, the results are the same

Table 14 Model 1 suitability scores for the best and worst restaurants in Profile 8

Restaurant	11	12	13	14	15	1
Best options						
Al Arz Delicias Arabes	0.71	–	0.54	0.57	–	0.61
La Trece Bistro	0.75	–	0.38	0.37	–	0.52
Worst options						
Yotojoro	0	–	0.4	0	–	0
La Tinaja	0	–	0.93	0	–	0

Table 15 Model2 suitability scores for the best and worst restaurants in Profile8

Restaurant	11	12	13	14	15	A
Best options						
Al Arz Delicias Arabes	0.71	–	0.4	0.57	–	0.57
La Trece Bistro	0.75	–	0.36	0.37	–	0.51
Worst options						
Yotojoro	0	–	0.4	0.29	–	0.2
La Tinaja	0	–	0.3	0	–	0.12

Table 16 Model3 suitability scores for the best and worst restaurants in Profile8

Restaurant	11	121	122	123		131	132	133	14	15	A
Best options											
Al Arz Delicias Arabes	0.71	–	–	–	0.06		0.55	0.57	0.57	–	0.57
La Trece Bistro	0.75	–	–	–	0.28		0.39	0.4	0.37	–	0.51
Worst options											
Mantequilla	0	–	–	–		0.14	0.42	0.62	0.29	–	0.2
Yotojoro	0	–	–	–		0.07	0.41	0.42	0	–	0.09

regardless of the type of calculation used because there is a single clear preferred option.

The compensatory effect of using only the weighted average operator is clearly seen in the results, especially for the worst restaurants, which can compensate for a very bad degree of suitability with others. The proposed architecture in Model 1 avoids this situation, giving a zero-suitability degree to restaurants that do not sufficiently satisfy some of the requirements.

The results of this study also show how the suitability functions can personalize recommendations to the preferences of each tourist type. In this way, it will ensure that each user obtains the best restaurant that suits his/her tastes. Moreover, variability in user profiles ensures that all restaurants have an equal chance of being recommended. This enhances the fairness of the recommendation, avoiding biases that can be found when using travelers' online reviews, as the number of reviews may not be comparable between a well-known restaurant and a new restaurant.

6 Conclusions and Future Works

Currently, many restaurant recommender systems use machine learning techniques to build models from large datasets, including textual user reviews. However, in emerging tourist destinations, such data may be scarce and insufficiently representative. This paper proposes a model constructed using a multi-criteria decision-aiding approach, based on the use of graded logic aggregation operators.

The use or conjunctive/disjunctive operators in a hierarchical way improves the evaluation of restaurants by modeling the simultaneity property when some requirements must be satisfied at the same time, as well as mandatory versus optional requirements. This model considering a hierarchy of criteria has shown to effectively represent the human logic reasoning of people when selecting a restaurant.

The model we propose is versatile and adapts to destinations of any size. It uses a reduced number of attributes to focus on relevant aspects of restaurant selection to build a system that may be easy to use. The set of criteria or their definitions can be changed depending on the relevant attributes of restaurants in other cities. The work follows a methodological procedure for the configuration of a restaurant recommendation system model supported by the LSP that can be used for other tourist destinations. The main stages to consider are data collection and processing, hierarchy definition and operator selection, as well as the definition of predefined options for suitability attributes adaptable to the user's needs.

Another key contribution of this study is the definition of the Food Specialty Interest Score (FSIS), which calculates the suitability degree of a restaurant in terms of an ordered list of food specialties, which is compared to a set of foods selected by the user. Such an indicator could be used in other systems to evaluate user satisfaction with respect to a multi-valued categorical attribute.

Experimental validation of the recommender has been done in Riohacha District, in Colombia, with a set of 8 diverse user profiles. A panel of three experts evaluated the system's recommendations for each profile. The results indicate that the proposed recommender system model achieves the maximum recall in comparison with other models. In particular, two simpler LSP models have been also used, and results show that the proposed model achieves better accuracy in the restaurants' recommendation.

In future work, we plan to implement a mobile application for the recommendation of restaurants in Riohacha and test it with real users to evaluate its functionality and usefulness in generating effective recommendations. In addition to the list of best restaurants, it is expected to include tips on tourist security, such as unsafe actions to avoid, telephone numbers of the tourist police, or costs of transport services in the city.

The proposed recommendation system has the potential to boost economic projections related to the promotion of gastronomic options, particularly in emerging tourist destinations. Such a restaurant recommendation system would not only contribute to improving personalized service practices for tourists but could also do so in contexts marked by significant economic constraints. The recommendation system has been developed with data from Riohacha-La Guajira, Colombia, a place often recognized nationally and internationally for its poor conditions, this technological solution could become a valuable opportunity to highlight local developments. In that sense, this system could benefit the Wayuu indigenous community by promoting their culinary activities and facilitating their recommendation to tourists visiting the region.

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Availability of Data and Material The data of the restaurants used in this study is available as additional supporting file in csv format.

Declarations

Conflict of interest Authors declare no competing interests.

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