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ORIGINAL RESEARCH

A logic multi-criteria recommender system for tourist services: Jimataa

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Abstract
Emerging tourist destinations face several challenges, including a lack of data on travellers, as well as indicators to strengthen the competitiveness of the city's services, reliability and tourist security. This paper describes a recommender system based on multi-criteria logic aggregation operators called Jimataa. The method of analysis is based on graded conjunctive-disjunctive operators and asymmetric assignment of a penalty or reward score regarding mandatory and optional criteria satisfaction. Several criteria are included for the evaluation of suitability, such as location, category, food specialities, other visitors scores, or services available. This system has deployed in Riohacha (Colombia) and it has been tested with end users by means of a survey. The web recommender system received a satisfaction rating of 86.42%, and the ease of data entry was rated with 77.78%. In the data entry process, 91.36% of users gave a maximum rating. These results indicate the efficiency of the system both in its recommendations and in the simplicity of the data entry process. This web recommender is a new technological product that can help emerging destinations by providing visitors with personalised, user-oriented tools and, on the other hand, improving the management of tourist services when providers do not have the capacity to maintain information on traditional platforms or social networks.

Keywords Artificial intelligence · Recommender system · Multi-criteria · Decision making · Logic scoring of preference · Web platform

1 Introduction

Recommender systems (RS) are relevant technological tools in several industries, as they process data and use advanced techniques to provide personalised suggestions based on users' tastes and preferences [1–3]. In the tourism sector, innovation in these systems has received much attention, as there are currently several models and typologies of these systems that aim to improve the traveller experience by tailoring products and services to the specific needs of each traveller [4, 5]. Web RS have proven to be particularly useful in various areas of tourism, such as accommodation, restaurants, transport and tourist activities [3, 6, 7]. However, challenges remain in improving the personalisation of recommendations in this Web systems, especially when taking into account destination context factors, security and the specific interests of users, especially in emerging destinations.

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Some of the most popular travel platforms in the tourism sector that are used when a tourist is new to a destination are web portals such as booking.com and TripAdvisor. Although these platforms are widely used to find suitable products (e.g. hotels, restaurants, etc.), they have limitations in terms of personalisation due to the use of general search filters and the lack of options to specify interests degrees, importance of each feature or mandatory/optional requirements related to the destination [3]. In this sense, there is a need to develop innovative architectures and designs that take into account more specific criteria and attributes, allowing a more detailed personalisation of the tourism services and products offered by a destination, which can help attract new visitors [8, 9]. Therefore, the development of this type of solutions is one of the first actions that emerging tourism destinations must take to transform themselves into smart destinations [10]. To achieve this transition, it is necessary to overcome data-related barriers, which are essential to design solutions based on artificial intelligence, and this involves consolidating a data-driven culture and facilitating informed decision-making [11, 12].

To address these problems, the innovative recommender system '*Jimataa*', whose name means 'to be calm' in Wayuunaiki (native language of the Wayuu people of the La Guajira peninsula in Colombia), has been developed. *Jimataa*© is a registered tool that helps to strengthen key indicators of tourism competitiveness, such as promotion and tourism security. The system is based on validated data on hotels and restaurants, ensuring the existence of reliable providers, and offers personalised recommendations adapted to the visitor's tastes, thus improving the user's tourism experience [3, 13].

Jimataa is based on Multi-Criteria Decision Aiding (MCDA) techniques, a research area dedicated to the development of decision support methods that take into account different, possibly conflicting, evaluation criteria to assess a set of alternatives, with the aim of differentiating them in terms of overall suitability and helping the user to make a decision [14]. To calculate the recommendation, our recommender system uses the Logic Scoring of Preference (LSP) evaluation method, which will be explained below [15]. The Web recommender system for hotels is based on information about their context, location, previous reviews and category [16]. On the other hand, in the case of restaurants, it can make suggestions based on tourists' food preferences, desired food type, location and other users' reviews, thus providing more accurate and personalised recommendations [17].

Jimataa was designed with the concept of security in tourism in mind. This aspect is extremely relevant to visitors as it directly affects their enjoyment and perception of the trip [18]. This concept encompasses the comprehensive protection of life, health, physical, psychological, logical and economic integrity of visitors, service providers and members of host communities [19]. Risk management and safety are fundamental concerns for any business in the tourism sector, including tour operators, hotels, attractions and festivals [20]. However, usually those aspects are not evaluated from a personal perspective in recommender systems. *Jimataa* addresses these issues by integrating security as a key element in data processing for recommender system design, thereby improving tourist confidence and satisfaction [21].

1.1 Goal and contributions

The main objective of this paper is to present how *Jimataa*, a web-based, multi-criteria recommender system for tourism services in Riohacha, Colombia. This system aims to promote local tourism and enhance the competitiveness of providers by ensuring reliability and tourism security, as well as by personalizing recommendations based on users' preferences. Offering safe and good recommendations in emerging touristic destinations is complex due to the lack of data from other travellers.

The contributions of the work are: (1) the design of a web platform based on logic multicriteria aggregation operators for tourist services as hotels and restaurants, 2) the recommendation model solely considers the user personal preferences by means of predefined suitability functions, not relying on the need of collaborative techniques, (3) the *Jimataa* tool only includes reliable providers validated by the local authorities, (4) it provides tailored information about the emerging destinations and security guidelines for tourists, and (5) the results of an onsite evaluation are presented, demonstrating the utility and quality of the *Jimataa* platform.

Section 2 present de related works. Section 3 presents the design and development of the recommender system. Section 4 presents the results and discussion of the design and development phases of the recommender system based on LSP, and the implementation and evaluation of the system with real users in Riohacha. The discussions are presented in Sect. 5 and conclusions in Sect. 6.

2 Related works

This section provides an overview of recommender systems on Tourism and the types of infrastructure used in their design, which follow from two previous works. In Solano et al. [13], we presented a review of hybrid recommender systems in the tourism industry, highlighting their application in hotels and restaurants. This literature review shows that the systems combine techniques such as collaborative filtering and content-based filtering to improve the accuracy and relevance of recommendations. In the context of hotels and restaurants, recommender systems take into account user preferences and contextual factors such as location to provide personalized suggestions. It also demonstrates the importance of integrating security into recommendations, an often-overlooked factor. The review shows that hybrid recommender systems can be designed for both web and mobile platforms.

In Solano et al. [3], we studied recommender systems in the tourism sector, highlighting their impact on personalising and improving the tourism experience. In the case of hotels, recommender systems found mainly rely on data from ratings and reviews to identify trends and improve the accuracy of recommendations, helping tourists to find accommodation that matches their preferences. In the case of restaurants, these systems use social media data to provide personalised recommendations based on users' culinary preferences, location and the opinions of other customers. These findings highlight the importance of integrating advanced technologies such as deep learning and data analytics to optimise recommendations and improve customer satisfaction in the tourism sector. In this line, the use of Multi-Criteria Decision Aiding models is increasing as they offer tools for a highly personalized user profile exploitation with a mathematically well-founded procedure for integration and balancing of diverse and conflicting preference criteria. Another dimension of interest is the availability of the recommender systems, with tailored front-ends for its use in both mobile and web platforms. Table 1 presents a review of the most recent recommender systems (since 2020), published in journals indexed in Web of Science. All them are focused on hotel (H) or restaurant (R) filtering by means of Web or Mobile applications. The table presents the general purpose of the work, the item recommended, a summary of the technique used for the recommendation, the platform and the type of criteria considered.

Table 1 shows a wide range of approaches aimed at improving the user experience and the accuracy of recommendations for hotels and restaurants. Among the techniques highlighted are collaborative filtering, which is used in 3 of the presented works. For example, matrix factorisation methods such as NMF and SVD, to capture complex interactions between users and items and improve restaurant recommendations, as seen in the Riyadh restaurant system [22]. Several systems rely on reviews of the hotels and restaurants. For example, they exploit sentiment analysis and semantic extraction from user reviews to enrich hotel recommendations, addressing challenges such as data scarcity for new hotels by weighting review volume and sentiment polarity [24]. In addition, multi-criteria decision-making methods (f.i. TOPSIS) and machine learning methods (f.i. clustering) have been applied to better model user preferences across multiple dimensions, such as environmental friendliness and service quality [25, 26].

Many publications on tourism recommender systems do not explain how the proposed techniques are integrated into a tool easily available to the user [30] s. Web and mobile platforms are nowadays used by almost any kind of possible visitor [31]. The studies shown in Table 1 not only present a recommendation technique, but also, they explain the user interface, which is a crucial component to achieve user engagement and satisfaction with the system. Mobile applications enable the consideration of context awareness and environmental features during recommendations. Web platforms are more appropriate to give interactive visualisations, which are used to assess the impact of tourism promotion and user acceptance of recommendations [23, 28]. The criteria used in the studies include user ratings, review quality, opinion, proximity to services, and contextual factors such as time and location, demonstrating a comprehensive approach to capturing user preferences and improving the

Table 1 Hotel and restaurant recommender systems

Ref	Purpose	Item	Techniques	Platf	Criteria
[22]	To develop a recommendation for restaurant selection in Riyadh, with optimized user experience.	R	Collaborative matrix factorization methods: NMF (Non-negative Matrix Factorization), SVD (Singular Value Decomposition)	Web	User ratings, number of evaluators, and review data quality
[23]	Evaluate the impact of tourism promotion campaigns through simulation and analysis of tourist flows.	H	Item-to-item similarity matrix	Web	Tourist preferences, regional impact, acceptance of item recommended
[24]	To extract tips from hotel reviews to improve recommendations, including new hotels with few reviews	H	Unsupervised semantic tip extraction algorithm combining review content and sentiment analysis, with weights based on review volume.	Web	Sentiment polarity in reviews and tips, number of reviews, hotel amenities, usefulness and novelty of tips evaluated by human annotators
[25]	To improve the accuracy and efficiency of hotel recommender systems by improving the user preferences modelling.	H	Multi-Criteria Collaborative Filtering, Naïve Naïve Bayes Multi-Criteria Collaborative Filtering (MCCF) Clustering ensembles with Self-Organizing Maps (SOM) Expectation-Maximization (EM)	Web	User satisfaction, including environmental friendliness and quality dimensions extracted from textual reviews and ratings.
[26]	To develop a ubiquitous tourism system integrating context-awareness and augmented reality, to recommend hotels near the user.	H	TOPSIS combined with clustering	Mobile app	Proximity to transport, restaurants, attractions; cost; stars; user context
[27]	To analyze tourists' preferences through online review analysis to understand decision-making in Malaysian spa hotels.	H	CART (Classification and Regression Trees) HOSVD (Higher-Order Singular Value Decomposition) Clustering: k-means y Self-Organizing Map (SOM)	Web	Service quality, user experience, and specific aspects extracted from review texts such as comfort, cleanliness, and staff behavior.
[28]	To propose recommender system that personalizes itineraries, including hotels and restaurants.	H &R	Content-based filtering Collaborative filtering Contextual filtering Social filtering Operational research techniques	Web & Mobile	Demographic attributes, contextual information (time, location, weather), social data, and user behavior patterns.
[29]	To develop a hotel recommender system that integrates images, reviews, and ratings, with text analysis.	H	Convolutional Neural Networks (CNN) Word2Vec Text CNN Latent Dirichlet Allocation (LDA) Sentiment Analysis Transformer's Multi-Head Self-Attention Mechanism	Web & Mobile	Review text, images (visual content and tags), user's ratings, and features such as service quality, hotel infrastructure, environment, and user experience
Our model [16, 17]	Jimataa: A multi-criteria recommender system that personalizes hotel and restaurant suggestions for tourists in emerging destinations	H &R	Multi-criteria aggregation operators, Logic Scoring of Preferences	Web & Mobile	Hotels: context, location, previous reviews and category. Restaurants: food preferences, desired food type, location.

relevance of recommendations in both the hotel and restaurant sectors.

The recommender systems reviewed in related works use various techniques such as collaborative matrix factorisation (NMF, SVD), clustering algorithms (k-means, SOM), classification methods (Naïve Bayes, CART), and advanced natural language processing tools (CNN, Word2Vec, transformers). In addition, many integrate sentiment analysis and multi-criteria collaborative filtering to improve personalisation, by exploiting the reviews and ratings collected from previous visitors.

The main limitations for the construction of tourism recommender systems, such as the scarcity of data and the limited technological infrastructure, make it difficult for emerging tourist destinations to transform themselves into smart destinations. Therefore, it is necessary to design and implement recommender systems that are adapted to the needs of such tourist destinations. Multi-platform (mobile and web) systems enable these emerging destinations to generate, manage and provide useful recommendation to every kind of visitor, thus facilitating decision making to strengthen their tourism potential.

The last row in Table 1 shows the features of the our Jimataa model, which has been designed for this particular kind of destinations where tourism is still not present. First, it is a platform that integrates both hotel and restaurant recommenders, with a unique Web interface that facilitates the use of the system with less input data requirements. It also presents a novelty by making use of the special advanced aggregation operators of the Logic Preference Scoring (LSP) method, which allows for a hierarchical and logical evaluation of user preferences. In this way, our model presents more relevant and personalised recommendations, especially in emerging destinations with limited data, clearly differentiating itself from other approaches.

2.1 Analysis of input/output data in hotel and restaurant recommender systems

Table 2 provides a comparison between our proposed model and other existing recommender systems in the tourism sector, regarding the kind of information that the user must introduce, the way it is used to model the user preference's profile, and the output that the system gives as result to the user. The same recommenders detailed in Table 1 are here analysed and compared to our system Jimataa.

Table 2 shows how each of the recommender systems analysed manages preferences based on user results, which in turn shows the results of the recommendations and how they are presented to the end user. Some models, such as those based on social platforms (e.g., Foursquare, booking.com, or TripAdvisor), collect implicit preferences from reviews and ratings, while others use explicit forms for users to define their criteria, such as types of transport, restaurants, or attractions. The results of these recommendation engines are displayed in lists and rankings, interactive visualisations, or detailed travel plans, demonstrating a wide range of approaches to personalising the tourist experience.

A logic-based, multi-criteria recommender system such as Jimataa model stands out because it allows users to assign customised weightings to each criterion and attribute using a form, facilitating precise adaptation to their individual preferences. Additionally, it integrates contextual data from hotels and restaurants, including location, categories, and dietary preferences, to generate a personalised list of the top three options, complemented by geolocation on Google Maps and safety recommendations, so that tourists can explore the tourist destination while enjoying its services. This combination of detailed personalisation and contextual support makes Jimataa particularly valuable for emerging destinations and for enhancing the user personalisation experience with careful and detailed guidance.

3 Design of the recommender system

This section describes the *Jimataa* architecture and its main components, together with the explicit and implicit information collected from users. It details the steps used by the system to make its calculations, which include the use of MCDA methods and, specifically, the LSP method to perform the mathematical calculations of the recommendation.

In the methodology used for its development, the SCRUM methodology was used for the development of the web application and the stages of analysis,

Table 2 Comparison of input/output data in web and mobile recommenders for tourist

Ref/characteristic	User preferences	Input	Output	Results provided to the user
[22]	User preferences are recorded through ratings and reviews collected from the social media platform Foursquare.com.	User-provided data on the web interface, including desired restaurant features and preferences (unlimited number of inputs)	Recommended list of restaurants with details such as name and address	Ranking
[23]	Based on real tourist choices, modeled with a multinomial logit model reflecting the probability of selecting known or promoted destinations.	Historical tourist arrival data Promoted tourist destinations (districts) Campaign parameters (e.g., conversion rates, promoted destinations)	Simulated tourist distribution across destinations Visualizations of simulation results and tourism trends	Interactive visualizations, including ranked lists of promoted destinations,
[24]	No explicit user preferences are collected; the system extracts useful tips directly from existing reviews without user input forms.	User hotel reviews containing textual opinions.	Concise and relevant tips extracted from reviews	Concise, sentiment-aware tips presented without lists or rankings but implicitly justified by analyzed opinions.
[25]	User preferences are recorded through multi-criteria ratings on social networking and tourism platforms, capturing detailed feedback on various aspects of items rather than a simple overall rating,	InputNumeric ratings per item, textual reviews	Predicted overall ratings or utility scores for items,	As ranked lists of relevant products or hotels, focusing on personalized relevance without explicit textual justifications.
[26]	Registered via forms in the interface where users input types of transport, restaurants, and attractions.	User location, user preferences (transportation, restaurant, attraction types), hotel candidate data including proximity, cost, category, context parameters	Hotels displayed on Google Maps, augmented reality visualization of selected hotel and nearby points of interest	Lists and rankings of hotels with contextual visualization via augmented reality, without detailed justifications.
[27]	Preferences are recorded by analyzing users' online reviews on TripAdvisor using machine learning techniques, rather than through explicit forms or questionnaires.	Online reviews and ratings	Predicted traveller preferences presented as rankings or lists of recommended spa hotels.	Rankings and lists of recommended spa hotels based on learned preferences, with implicit justifications derived from review analysis.
[28]	Preferences are captured through user profiles including trip purpose, types of items consulted, ratings, and contextual data such as location and time; likely gathered via interactive forms	User profile modules including preferences, demographic attributes, contextual data (time, space, location), social data, and past interactions	Personalized itinerary recommendations presented as ranked lists and detailed trip programs with contextualized suggestions	Detailed trip programs rather than simple lists; recommendations include rankings and contextualized suggestions to help tourists plan their itinerary effectively
Our model [16], [17]	Using a form, the user assigns weights to each criterion and attribute to tailor the recommendation to their preferences.	Hotels: context, location, previous reviews and category. Using Bookim.com Restaurants: food preferences, desired food type, location. Using Tripadvisor	OutputPersonalized list of top hotels and restaurants, geolocated with Google Maps to guide tourists, along with safety recommendations.	A list is presented with the three best hotel/restaurant options that match the users' preferences.

design, implementation and evaluation of the web development for the recommender system based on LSP for the tourism sector were followed. The following are some of the activities conducted during the development stages of the system. The following is a detailed description of each stage and activity carried out during the construction of this multi-criteria web recommender system for hotels and restaurants.

3.1 Analysis

At this stage, we established both functional and non-functional requirements for designing recommender systems. We conducted a comprehensive review of existing recommender systems, which enabled us to identify the features required to configure the new system. Consequently, we defined the requirements based on the specific needs of our solution and the features necessary to meet these needs effectively. This review highlighted best practices, identified opportunities for improvement, and provide a solid foundation for developing an innovative system tailored to the unique context of an emerging tourism destination.

3.1.1 Functional requirements

Functional requirements are defined in terms of the specific capabilities the system should provide to meet user expectations and interests. These included:

- Personalisation of Recommendations. The system must be able to generate personalised recommendations based on user preferences and behaviours.
- Intuitive interface. A user-friendly interface is required to facilitate interaction and identification of preferences through dynamic forms.
- Tourism security aspects. The system may include only providers who are validated and recognised by competent entities in the destination and must also provide information for tourists to carry out the activity safely.

3.1.2 Non-functional requirements

The non-functional requirements addressed aspects such as the efficiency, scalability, and security of the system.

- Efficiency. The system must be able to process data and generate recommendations in a reasonable time according to the user's taste.
- Scalability. The system architecture should allow for expansion to handle an increasing number of users and data without performance loss.
- Security. The protection of users' personal data and integrity of the processed information must be guaranteed. Therefore, the data completion version was defined as optional.

3.2 Design and development

In this stage, a thorough analysis was conducted to select the most appropriate tools and technologies for recommender system architecture using the SCRUM methodology. Various components were evaluated, including the database management system, framework for web application development, frontend and backend. This selection was relevant for ensuring a robust and efficient architectural design capable of supporting both the construction and effective operation of the recommender system.

Regarding the web development, the following tools were selected:

- Database management system: A relational database management system was chosen for its ability to handle large amounts of structured data and its efficiency in executing complex queries. The database management system chosen was PostgreSQL, which is object-oriented, relational and open source.
- Web Application Development Framework: A web development framework was chosen to facilitate the creation of scalable and sustainable applications. This framework should allow integration with various technologies and provide tools for agile development according to the SCRUM methodology. In our framework we chose Express.js in the backend, Angular material and Bootstrap in the styles.
- Front-end tools: For the front-end development we chose technologies that allow the creation of intuitive and responsive user interfaces. We chose Angular for the front-end and the Google Maps library for Angular. These tools should facilitate the user's interaction with the system, allowing for a smooth and pleasant experience.
- Back-End Tools: On back-end, data processing, user modelling and product recommendation will be done by employing multi-criteria logic-based aggregation model known as LSP [15], which makes use of Artificial Intelligence principles of symbolic and uncertainty reasoning. In LSP, Graded Logic (GL) is used to model the logical reasoning process during human decision making that usually works with a logical aggregation structure in the form of a tree of criteria. The tree has a set of elementary attribute criteria (leaves) with their corresponding partial suitability score, and a set of non-elementary criteria (intermediate and root nodes), with an associated aggregation operator that calculates the suitability value of that node from its direct descendants. Aggregation is performed with graded conjunction/disjunction (GCD) operators because they allow modelling the degree of simultaneity level required at each node, from full simultaneity (conjunction) to full substitutability (disjunction). The GCD aggregator has 17 different levels and, for the purposes of our models, we select the

most appropriate operators to best customize the recommendations [15].

3.3 Implementation and evaluation

The implementation was conducted in the municipality of Riohacha, La Guajira, Colombia. It is an emerging tourist destination with the necessary conditions for the implementation of this kind of web-based recommender system, as it has a large number of both hotels and restaurants. The software implementation of the *Jimataa* system has been done at Universidad de la Guajira. After the implementation, the platform was presented to members of the community and tourists at the tourist destination the city of Riohacha, La Guajira, Colombia.

A group of 86 users was selected to test the performance of this web recommender system for both hotels and restaurants. The evaluation was carried out between January and March 2024. Simple random sampling was applied to select a representative sample of tourists present in the District of Riohacha during the study period, as well as visitors and members of the local community.

Each user was given a survey to answer after using *Jimataa*, which included the following questions: (1) On a scale of 1 to 5, were the recommendations of the system adequate?; (2) Did the recommender system help you select the products/services you needed?; (3) How satisfied are you with the variety of recommendations offered?; (4) Was it easy to enter the information to obtain the recommendations?; and Would you recommend this system to your friend?

4 Proposed recommender system: JIMATAA

This section presents the results of the web development (architecture and the evaluation conducted by users who tested the recommender system. It must be noted that *Jimataa* has been designed to be used by Web access both from a computer and from a mobile phone.

4.1 Architecture of the Jimataa recommender system

The technical aspects of the system include several key components, such as (1) data collection and preprocessing, (2) modelling of user requirements, (3) the process of computing recommendations using LSP, and (4) the presentation of recommendations on the front-end web page.

Figure 1 presents the components of the recommender system and shows the user interaction with the front-end, starting with the form for registering tastes and preferences. It also shows how the system presents the recommendations, along with location and security information, on the front-end itself. The following subsections describe the technical details of these processes.

4.2 Data collection and preprocessing

Data collection and preprocessing are key stages to build a recommender that only includes safe providers and reliable information. Initially, the data has been obtained from publicly available sources, such as TripAdvisor, Booking.com, and Google Maps. To verify the legal status of the hotels and restaurants, a database provided by the Chamber of Commerce of La Guajira was used. It is an entity responsible for facilitating the registration and formalization of economic activities in the country. This database is restricted and can only be accessed with prior authorization from the entity. Using this information, the legal registration of the establishments included in the recommender systems was verified.

For the hotels, several relevant features were extracted from Booking.com. These included: sustainable travel programs, acceptance of credit card payments, availability of security cameras, breakfast service, availability of communication in English, the establishment's category (in COP), and the rating given by visitors, using a scale from 1 to 10 [32].

Regarding the location criterion, distances in meters were calculated from the hotels and restaurants to various points of interest. This procedure was carried out manually by local experts using Google Maps, to

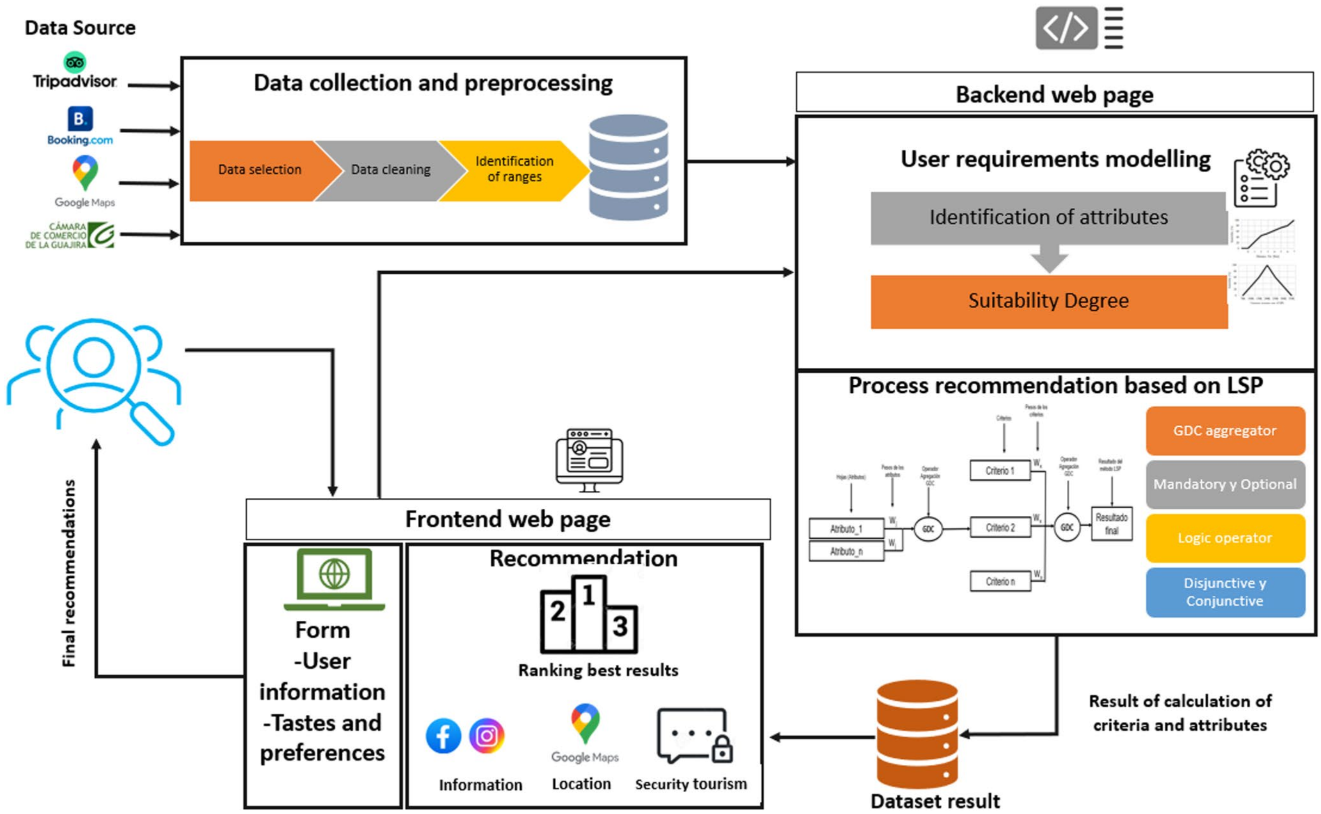

Fig. 1 LSP-based recommender system architecture model

identify the shortest and safest routes to the destinations. The geolocation data included variables such as distance to the beach, to the historical area of the city, to the pier and tourist police, and to medical services.

For the restaurants, data was extracted from TripAdvisor using web scraping techniques. The collected information included features such as food specialties (in the form of a list of food names), acceptance of credit card payments, availability of delivery service, and the option for vegetarian food (Yes/No). Additionally, the restaurant category and customer rating were recorded, using a scale from 1 to 5. Although the data extraction was automated, a manual process was carried out to categorize the information and adapt it for the modelling process [33].

After the data collection, a careful process of data curation has been done, consisting of selection, cleaning, and definition of the ranges of variables to be used in the analysis.

4.3 Back-end processes of the recommender system

This section presents user requirements modeling and the LSP recommendation method for the calculation of the recommendations with Artificial Intelligence reasoning mechanisms.

4.3.1 User requirements modelling

All the features collected in the previous task will be used for the recommender system to evaluate the suitability of each option (hotel or restaurant) for each particular user. Figure 2 presents the hierarchical structure of the criteria for the hotel and restaurant recommender systems [16, 34].

In order to make a personalized evaluation, user's preferences on the different criteria must be collected and modelled in the system. In this regard, during the

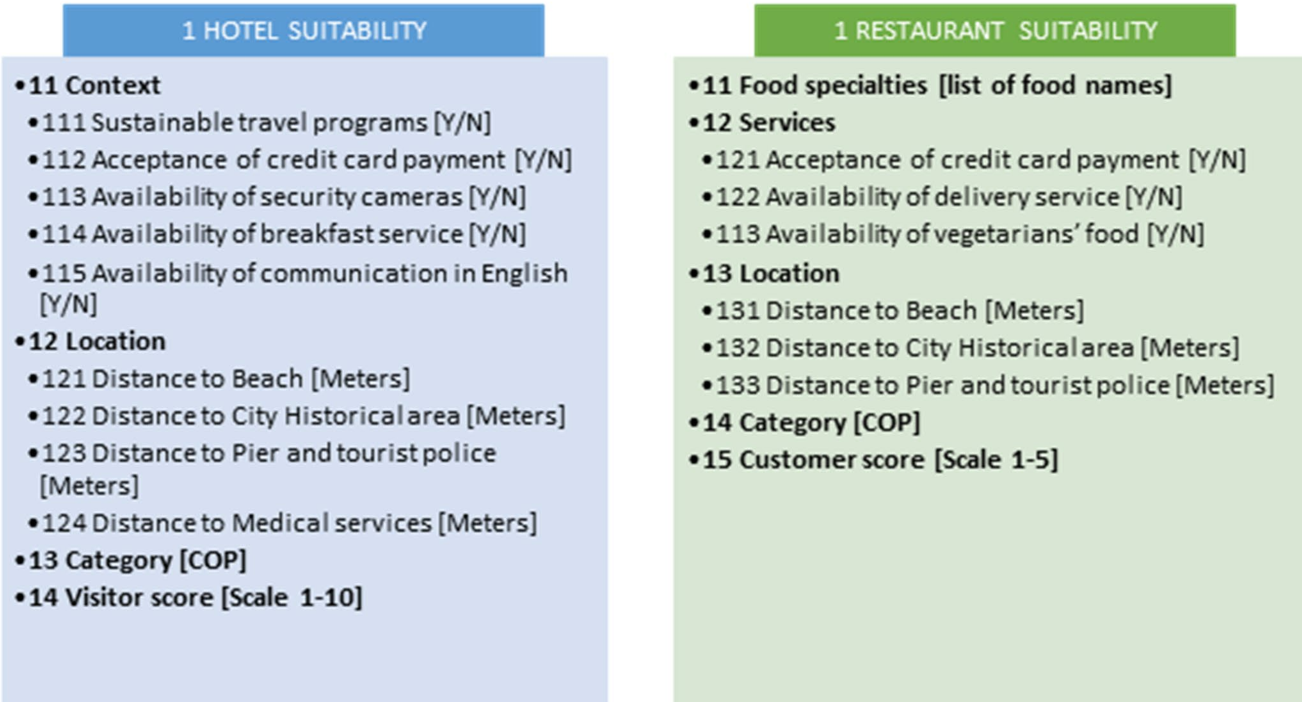

Fig. 2 Criteria for hotel and restaurant recommender systems [16, 34]

interaction with the web page, the user will be asked to introduce different kind of information that will be used to tailor the decision. Firstly, he/she must assign a weight to each criterion in the model, on a scale of 0 to 1.0, according to the importance or degree of interest they have for each criterion. Secondly, the contextual and services attributes will be presented to the user through specific questions, where the user will be able to select options such as “mandatory” or “optional” to determine which of them are indispensable. Thirdly, the system will prompt the user to choose from options of values for some other attributes, in order to know which are his/her preferences, such as " Economic”, “Expensive” or “Average cost” for price-related criteria; the user will be able to indicate which are the preferred score values form the ones given by previous users by choosing from “Excellent”, “Outstanding” or “I don’t care”; and for location criteria, the user will be able to choose from “Near”, “Medium” or “Far” distances. These choices allow the recommendations to be tailored to the user’s preferences and priorities.

The mathematical representation of these concepts in terms of suitability score is made using a set of predefined functions, which have been defined by local experts taking into account the characteristics of Riohacha. The suitability score is a measure to evaluate how well an alternative satisfies a specific criterion requested by the user. It represents a degree of truth, which is expressed by means of a numerical function that allow us to handle subjective information in a more flexible way. The use of predefined functions avoids asking to the user too much information, while it also permits to have a dynamic and adjustable model for representing different types of user preferences. Each suitability function reflects different degrees of preference in relation to a reference scale, defined similarly to fuzzy membership functions, but in our case satisfaction is expressed as 0 to 1.0 [16, 34]. Users can choose between three options for each criterion. For example, the suitability score for **location** in both systems was categorised as near (less than 1000 m), far (more than 5000 m), and medium (between 2000 and 4000 m). These categories were established according to the size of the analysed city, which is a small tourist destination.

For the **hotel category**, the degree of suitability was based on the average prices measured in Colombian pesos (COP), with three options: economic (COP < 150 K), expensive (COP >300 K), and average cost (COP between 170 K and 230 K). For restaurants, user satisfaction was measured in terms of **price range**. Users are satisfied with an economical cost if it is below COP 40,000, with an expensive option if it is above COP 80,000, and with an average cost category if the price is between COP 45,000 and 65,000.

In the case of **visitor ratings for hotels**, the degree of suitability is defined in two options: 'excellent' (9.4–10) or 'very good' (7.5–9.3). For restaurants, an 'excellent' score is considered satisfactory if the restaurant has a **rating between** 4.5 and 5.0, while the 'very good' option is acceptable with a score between 4.0 and 5.0, being less demanding. In addition, for this attribute, the option 'I do not care' is included for more flexibility.

Details of these suitability functions can be found in [16, 34]. Additionally, the paper [34] introduces the Food Specialty Interest Score (FSIS), an indicator that measures the alignment between a user's preferences and the food specialties offered by a restaurant. This score helps evaluate how well a restaurant's culinary offerings match an individual's tastes and preferences, thus providing a key measure for personalizing recommendations. The Food Specialty Interest Score (FSIS) is an indicator that measures the correspondence between a user's preferences and the food specialties offered by a restaurant [34].

4.3.2 Logic scoring of preference recommendation method

After defining the criteria and establishing the degrees of suitability, the backend component of our system can calculate which is the suitability score for each criterion and alternative (i.e. hotel or restaurant) for a given user. The next step consists in merging the scores of all criteria to obtain an overall suitability score for each alternative. Then, the overall scores will be used to make the filtering and recommendation to the user.

Table 3 LSP operators used for model criteria

Type of polarization	Level of polarization	Symbol	Orness	Andness	Attribute
Aggregation operators for Restaurants					
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	Restaurant
Aggregation operators for hotels					
Conjunctive	Strong	C+	0.125	0.875	Context - mandatory
Average	Neutral	A	0.5	0.5	Context - optional
Disjunctive	Very weak	D-	0.562	0.437	Location
Conjunctive	Medium	CA	0.25	0.75	Hotel

The merging of the partial suitability scores is done using the methodology of LSP. It consists on using graded logic aggregation operators at each of the composite nodes of the criteria hierarchy. In particular, we will use Graded Conjunctive Disjunctive (GCD) operators, because they permit to establish different levels of compensability between the criteria, which is characterised by the degree of orness/andness. GCD aggregators can be defined in various ways. In this work, we take the definition based on the 17 different levels given in [17], denoted as C, C++, C+, C+-, CA, C-+, C-, C-, A, D-, D-, D-+, DA, D+-, D+, D++, D. They range from full conjunction (C) to full disjunction (D), where A (the arithmetic mean) denotes logic neutrality.

Depending on the degree of simultaneity (andness) or substitutability (orness) of each high-level criterion, an appropriate operators was selected [16, 34]. The proposed operators used in the recommender system *Jimataa* are the given in Table 3.

Several functions can be used to implement a GCD aggregator [15]. To calculate the score based on the weights w_i given by the user and the suitability score x_i for each attribute, we used the weighted power mean (WPM) function (Eq. 1).

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

For the case of Service (in hotels) and Context (in hotels), an asymmetric aggregation is done. In this case, the recommender applies a compound operation denoted as CPA (Conjunctive Partial Absorption), that performing WPM and harmonic mean calculations [15, 34].

Following the hierarchy of criteria in a bottom-up procedure, these operators aggregate subsets of criteria into more general suitability scores for each user. At the end, each hotel and restaurant receive an overall suitability score that takes into account the user's preferences and priorities, as well as his/her requirements on mandatory features.

4.4 Jimataa recommender front end interface

In the recommender system interface, a form specifically designed to capture user tastes and preferences has been developed. Table 4 details the attributes and specifications that the users must complete in the input data forms. The basic personal user information is optional, except for the e-mail address, which is mandatory to manage interaction with the system. The rest of attributes, corresponding to general criteria and the deepening of interests by criteria are mandatory components, as they are necessary to personalize the recommendations and adapt the suggestions to the user's preferences. Finally, the system interface displays recommendations to the user, based on the established criteria and the information provided.

The results that the system presents to the user include a ranking of the three hotels or restaurants that match the user's tastes; to facilitate the location of these establishments, an interactive map is provided, generated through the Google Maps API. Following the input/output data presented in Table 4, the rest of the section will detail how the system works, explaining how the user data is captured through its graphical interface (desktop and mobile version) to perform the corresponding calculations.

The first thing the system asks users for is personal information. This information is completely optional, and the only mandatory field for the system to function correctly is the user's email address, see Fig. 3. The requested data includes: first name, last name, second last name, email address, gender, nationality, age range, and educational level.

Table 4 Input and output data of the recommender system

Components	Hotels		Restaurants	
Basic user information (Optional)	First Names First Surname Second Surname E-mail address Gender Nationality age range Educational level		First Names First Surname Second Surname E-mail address Gender Nationality	
General Criteria (Mandatory)	Context Location Category (based on price) Visitor score (The user defines their interest in 0–1)		Food specialties Services Location Category Customer score (The user defines their interest in 0–1)	
Deepening of interests by criteria (Mandatory)	–		**Food specialties**	[list of food names]
	Context	(User can select Mandatory or Optional)	**Services**	(User can select Mandatory or Optional)
	Location	Atritute questions (User can select Near, Medium or Far)	**Location**	Atritute questions (User can select Near, Medium or Far)
	Categoría (base on price)	(User can select the option Economic, Expensive or Average cost)	**Category** [COP]	(User can select the option Economic, Expensive or Average cost)
	Visitor score	(User can select the option Excellent, Outstanding or I don't care)	**Customer score**	(User can select the option Excellent, Outstanding or I don't care)
Recommendation to the user	Ranking of the 3 hotels/restaurants that match the user's preferences Access to the website or social networks of the hotels/restaurants. Recommendations for tourist security in the tourist destination. Name, telephone number, type of entity, location and ranking of emergency services (hospitals and police quadrant). Guide map to get to the site - using Google Maps API			

Although personal information is optional, this data is used to personalize the user's experience within the system. The data collection elements have been designed to be user friendly and easy to manage.

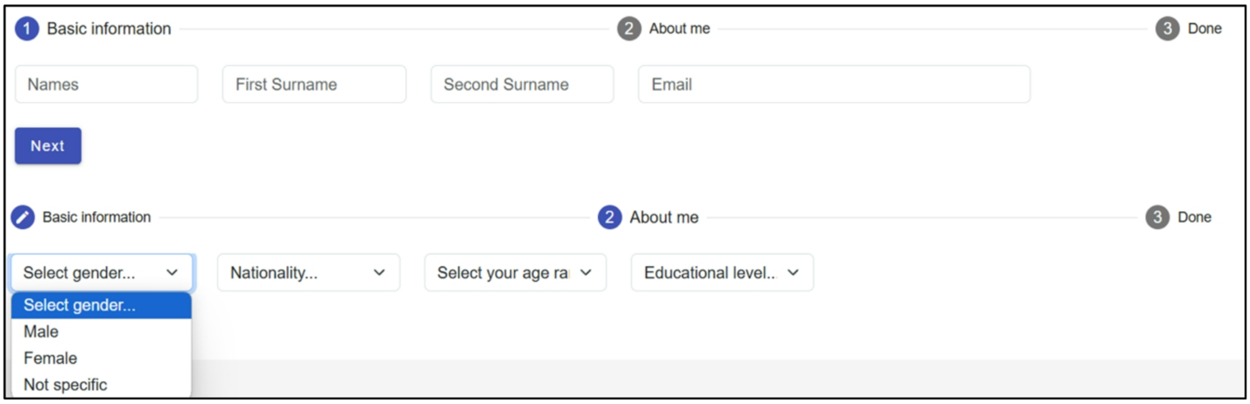

Fig. 3 Basic user information recommender systems

Figure 3 shows the next step of the process. In this stage, users must assign a weight by ranking the hotel features according to their relevance. To do this, the user is asked to indicate the degree of importance of each criterion by means of a scroll control. The scale ranges from “Indifferent” (the lowest value) to “Very important” (the highest value). Once the user has assigned their values, an internal calculation is performed to convert the representation into a number between 0 and 1. It is important to note that the sum of all the weights of the general criteria must equal 1 for the aggregation operations, but this property is transparent to the user as it is internally normalized. These weights serve to model the user’s preferences and interests, helping in the recommendation of hotels or restaurants that best fit their needs.

Figure 3 shows that the recommender system takes into account different criteria for hotels and restaurants. In the case of hotels, the general criteria include: Context, Location, Category (based on price), and Visitor Score. For restaurants, the criteria are: Food Specialties, Services, Location, Category, and Customer Score.

Figure 4 shows the interface for capturing data related to the Context (Hotel) and Service (Restaurant) criteria in *Jimataa*. This interface allows users to indicate which are the elements that must always be satisfied by the recommended hotels or restaurants. This information enables the system to accurately assess and recommend hotels or restaurants that satisfy the essential requirements of the user, avoiding unsatisfactory proposals that may highly satisfy many other criteria but that will not be acceptable for the user.

Figure 5 shows that, both in the context of hotels and restaurant services, a similar structure is used to capture user data. The questions posed in both interfaces are designed to make the criteria more understandable and user-friendly. For example, in the context of the accommodation experience, the user may be asked whether they prefer the hotel to have certain specific features. Some of these questions might include: Is it important for you that the hotel implements a sustainable travel program? Would you like the hotel to accept credit card payments? Would you prefer the hotel to have security features, such as surveillance cameras? Is it relevant for you that the hotel offers breakfast? Finally, would you prefer the hotel staff to speak in English? These preferences can be marked as Mandatory or Optional, allowing the hotel/restaurant to better align with the user’s needs and expectations.

Figure 6 shows the interface for capturing location data. The same structure is used for both hotels and restaurants. The user is asked about the hotel’s proximity to several points of interest, such as: How close would you like the hotel to be to the beach? How close would you prefer the hotel to be to the historic centre? How close would you like the hotel to be to the tourist police? How close would you prefer the hotel to be to a clinic? For each of these locations, the user can select from the options Near, Medium, or Far, helping to find a location that best suits their plans and needs during the stay.

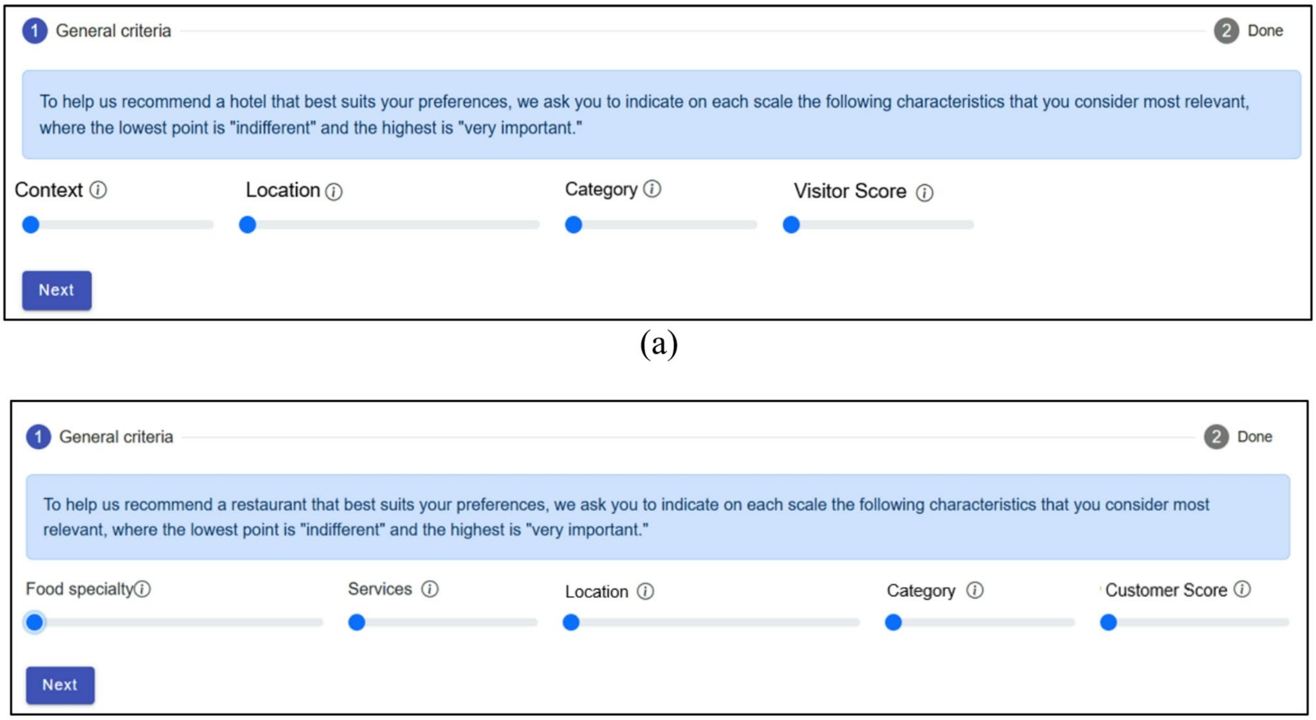

Fig. 4 General Criteria for Recommender Systems: (a) Hotels and (b) Restaurants

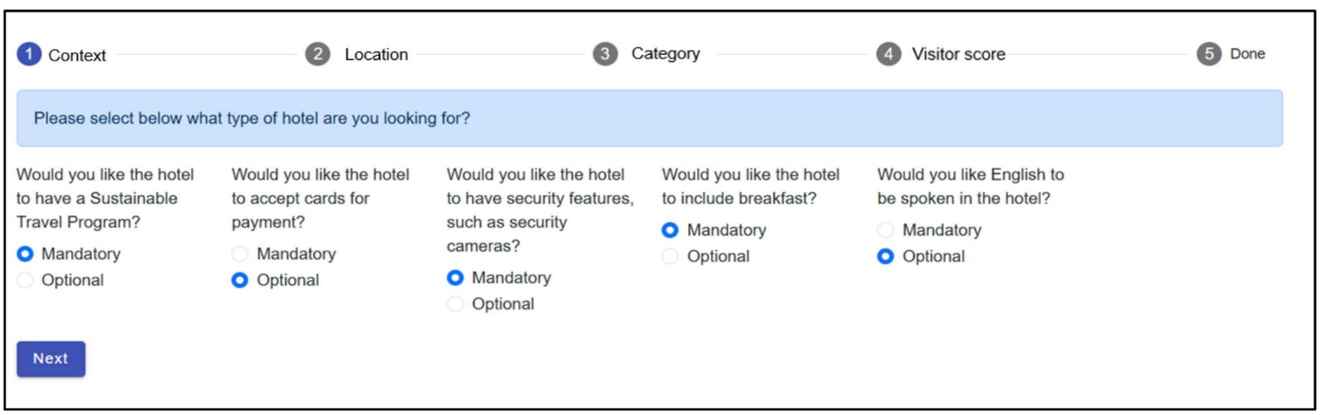

Fig. 5 Data Capture of Context (Hotel) and Service (Restaurant) in Recommender Systems

Figure 7 shows how the *Jimataa* tourism recommender system interface asks the user to register their preferences regarding hotel and restaurant categories. To better understand the user's preferences, questions like the following are used: What price range per night would you prefer the hotel to be in? The available options are Economy, Medium Cost, or Expensive.

Figure 8 shows the data capture for visitor scores (hotels) and customer scores (restaurants) in a recommender system. These scores are used to evaluate user satisfaction and help personalize recommendations based on previous experiences and reviews. The system allows users to select their preferred rating ranges to personalize suggestions based on their quality and price expectations. For hotels, the categories are: "Excellent" (9.4–10), "Outstanding" (7.5–9.3), and "Indifferent" for any other rating. For restaurants, the categories are: "Excellent" (5.0-4.6), "Outstanding" (4.5-4.0), and "Indifferent" for other ratings. Users simply choose one of these options for each type of establishment, helping the system filter recommendations that best match their preferences.

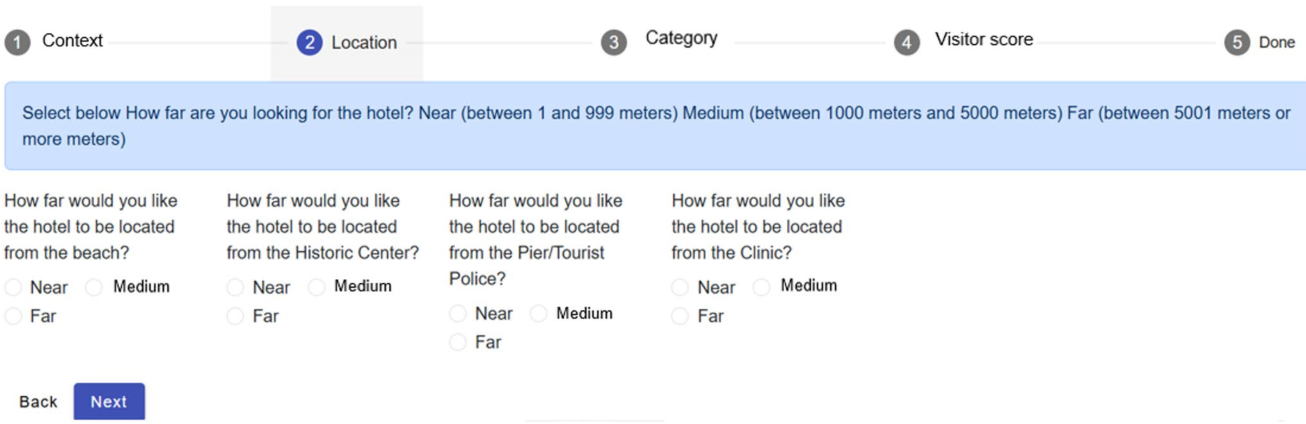

Fig. 6 Data of location for hotel and restaurant recommender systems

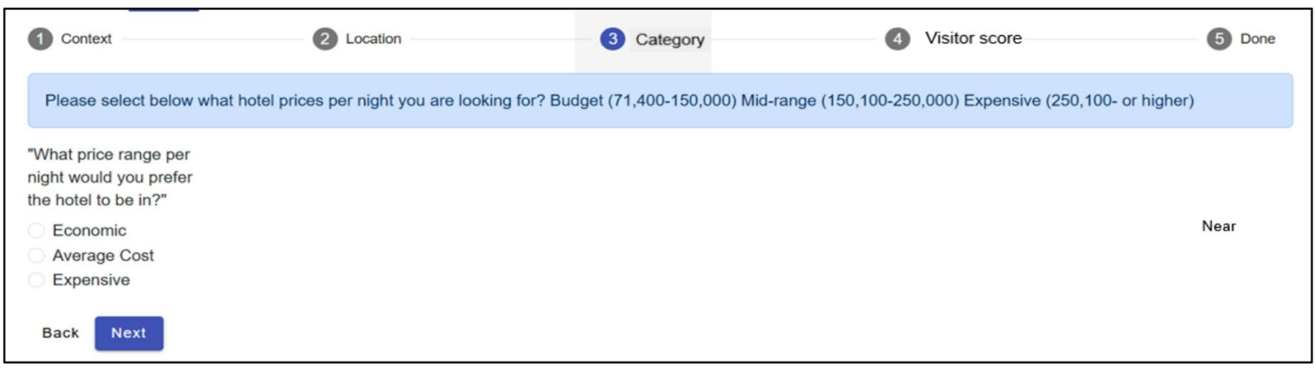

Fig. 7 Data of category for hotel and restaurant recommender systems

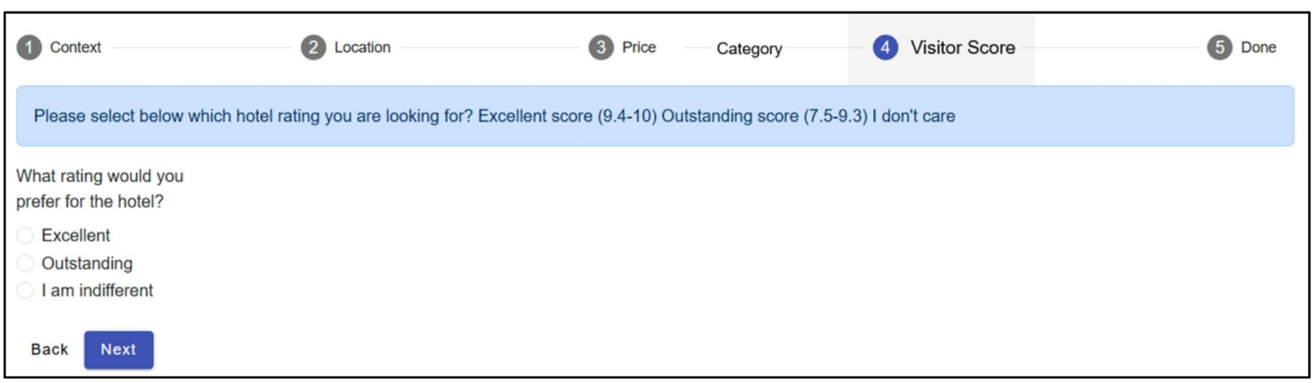

Fig. 8 Data of visitor score (hotel) and customer score (restaurant) in recommender systems

User interaction is made easy through simple questions like, "What rating would you prefer for hotels/ restaurants?", with response options such as "Excellent", "Outstanding", or "Indifferent". These responses enable the system to tailor recommendations according to the user's expectations for quality and price, improving the search experience. In this way, the system ensures that users receive suggestions that align with their preferences.

In the case of the restaurant recommender, Fig. 9 shows the food list and categories in the recommender system, where a classification of multivalued categorical data is performed. This classification assigns one or more categories to each food item, helping the system make more accurate recommendations based on user preferences.

Figure 10 shows how the system captures categorical data to identify the types of food the user wants.

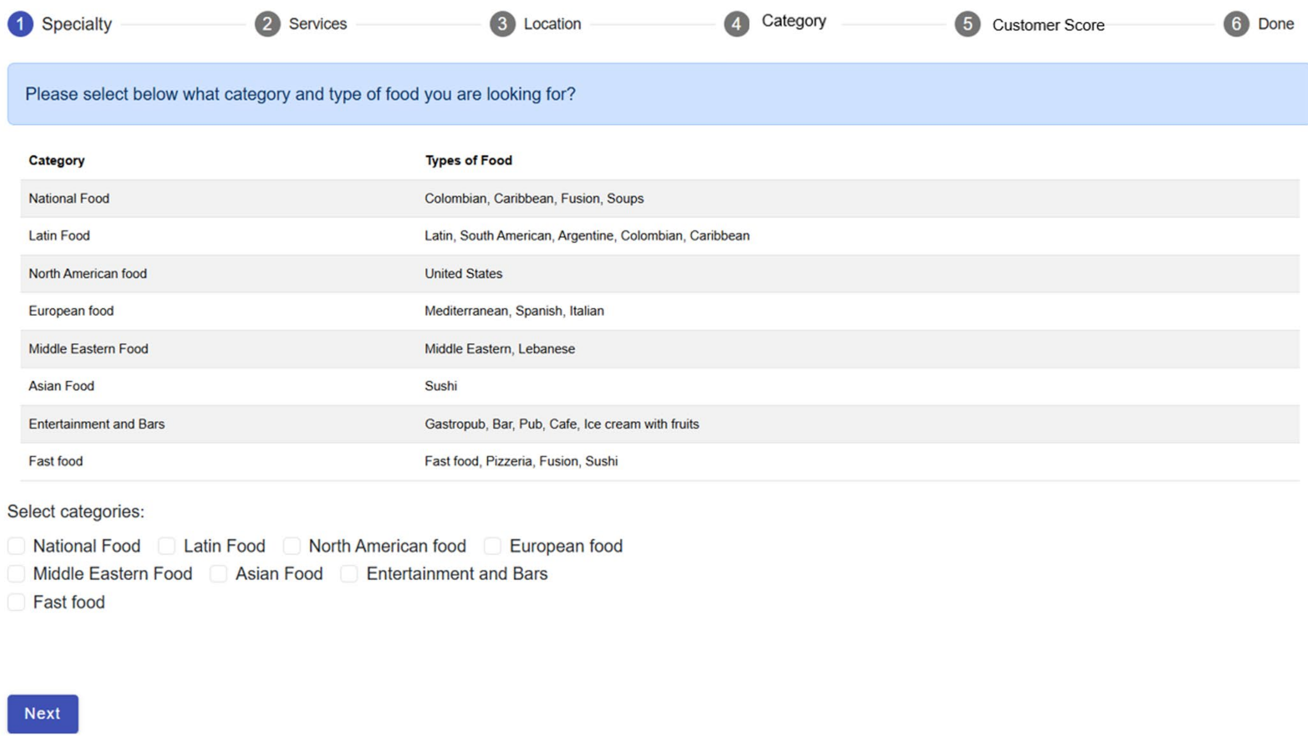

Fig. 9 Food List and Categories in the Restaurant Recommender System

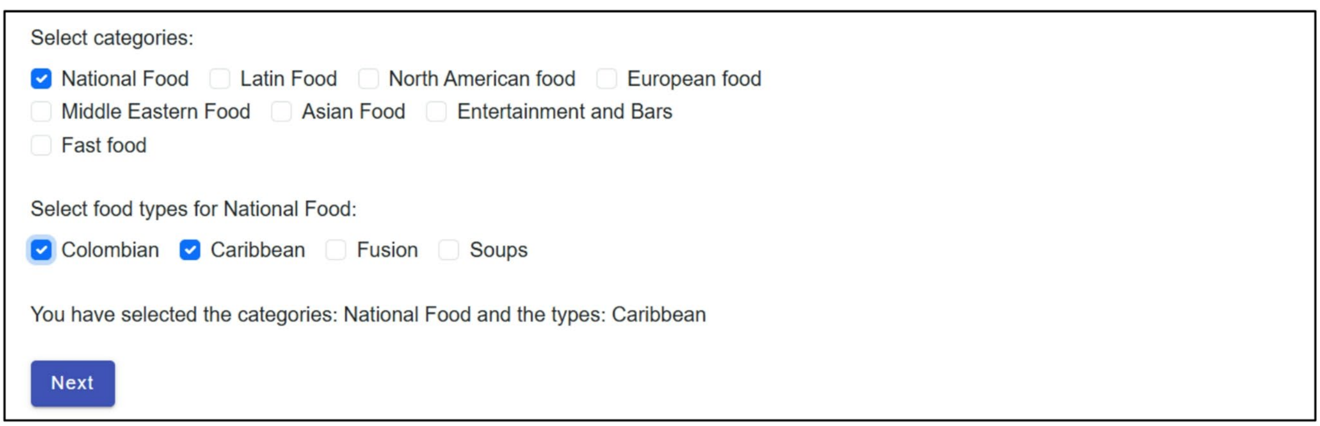

Fig. 10 Data Capture for Food Types in the Restaurant Recommender System

Selection boxes have been defined for this process. First, the user selects the food categories, which then activate additional selection boxes for the food types within each category. This allows the user to specify which types of food they are interested in, enabling the recommender system to perform the necessary calculations and provide more accurate recommendations based on their preferences.

Figure 11 shows the graphical interface of the mobile recommender system. It shows the interface of the system, including the selection of criteria, the response to the contextual criteria and the final results. This interface is the same for both the hotel and restaurant recommendater systems.

Figure 12 shows the recommendation results in the *Jimataa* web interface, both for hotels and restaurants. The recommendations are presented in a similar way, displaying the top three options that match the user's preferences, along with a match percentage based on the calculations from the recommender system. The names of the recommended hotels or restaurants are also provided. Additionally, a link to the establishment's website is included, as well as access to the

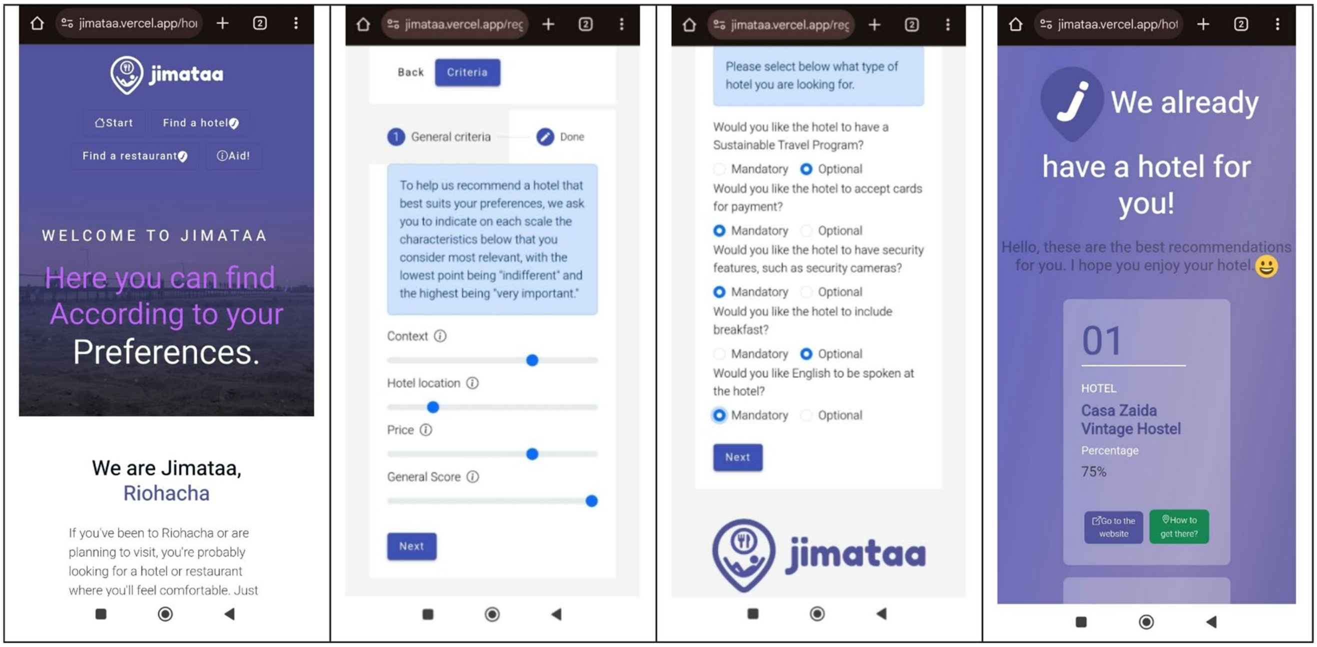

Fig. 11 Screenshots from the *Jimataa* system from mobile phones

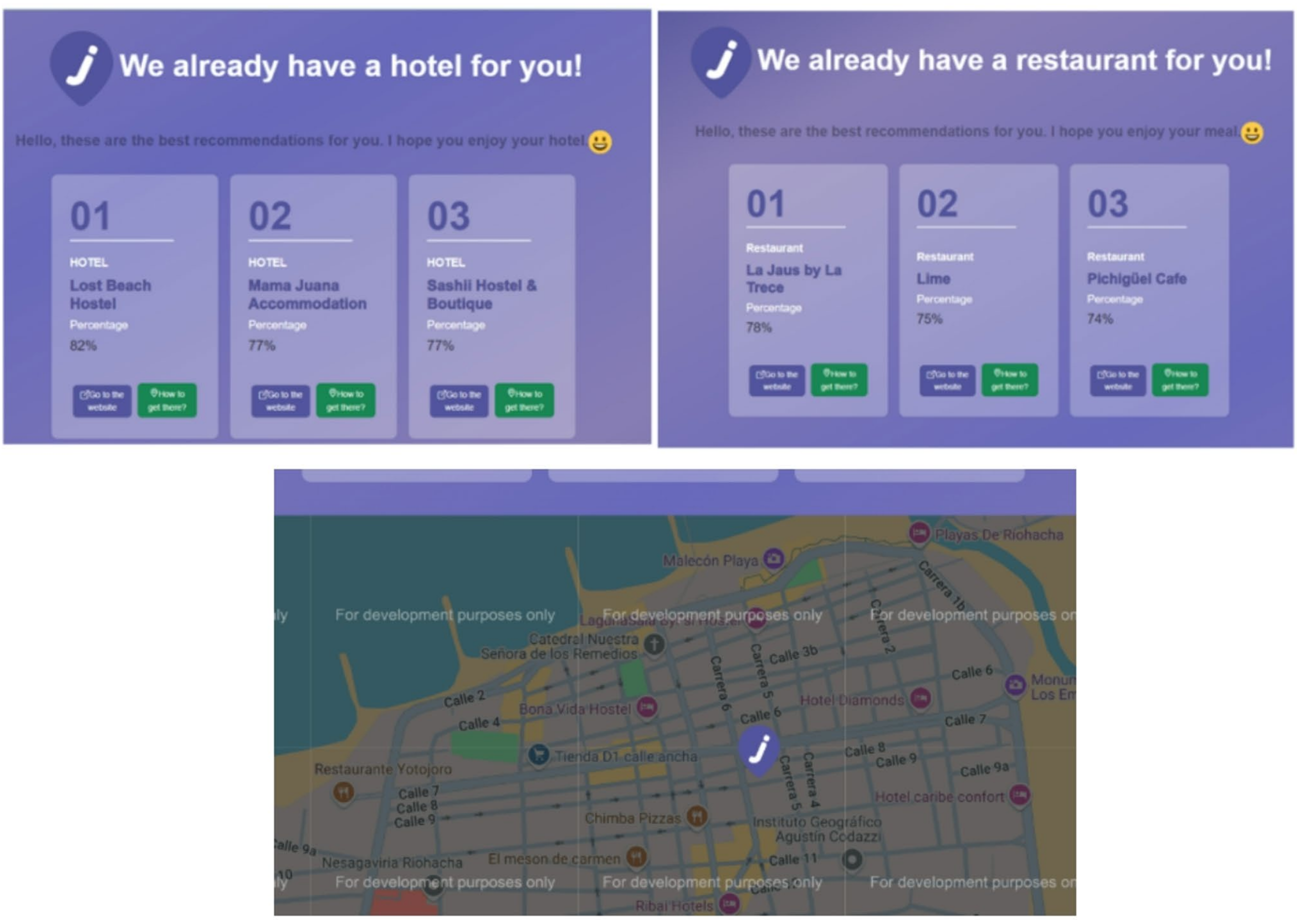

Fig. 12 Recommendation Results of the *Jimataa* Web Interface

Google API, to give users directions on how to reach the recommended destination.

Figure 13 shows a relevant aspect of our recommendations for users as information on tourist security at a destination. In particular, we provide practical advice to ensure safe stay in Riohacha. This includes guidance on what to do in the case of theft, how to handle illness situations, and how to safely get around the city. We also offer additional recommendations on tourist safety so that you can enjoy your trip with the peace of mind and confidence. Figure 14 shows the interface of how tourist security information is displayed in the mobile version of the *Jimataa* recommender system.

4.5 Experimental evaluation in Riohacha

In total, 86 people participated in the study. The methodology for answering the survey was that participants first had to test the recommender systems. Once they had obtained the results, they completed a questionnaire in which they provided their perceptions and evaluated the system. Table 5 lists five users who used the hotel recommender system, showing their selected weights and interests for each criterion and attribute.

Table 5 illustrates how different users (Users 1 to 5) interact with the system by assigning weights to

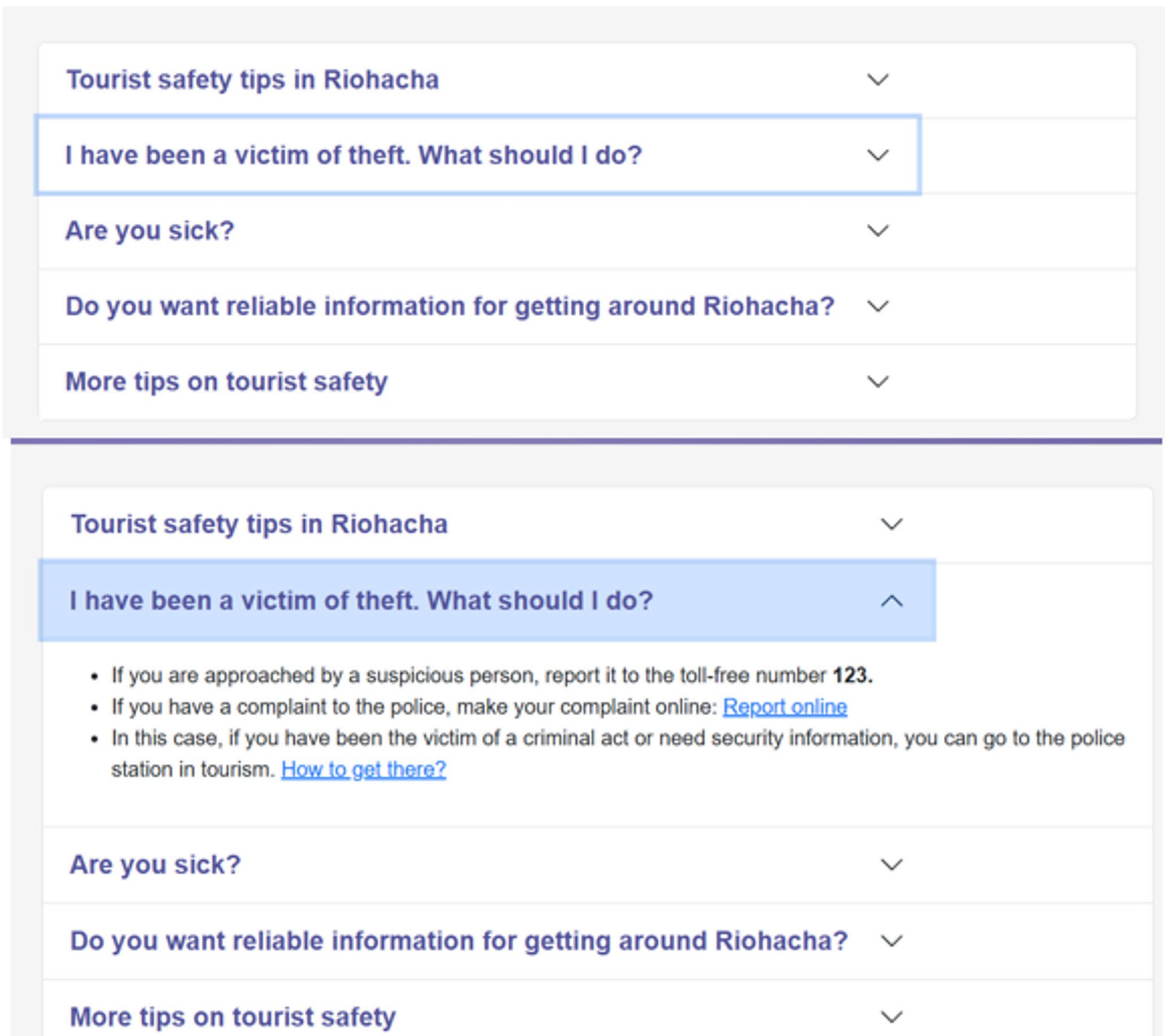

Fig. 13 Tourist security information in the Jimataa Web system

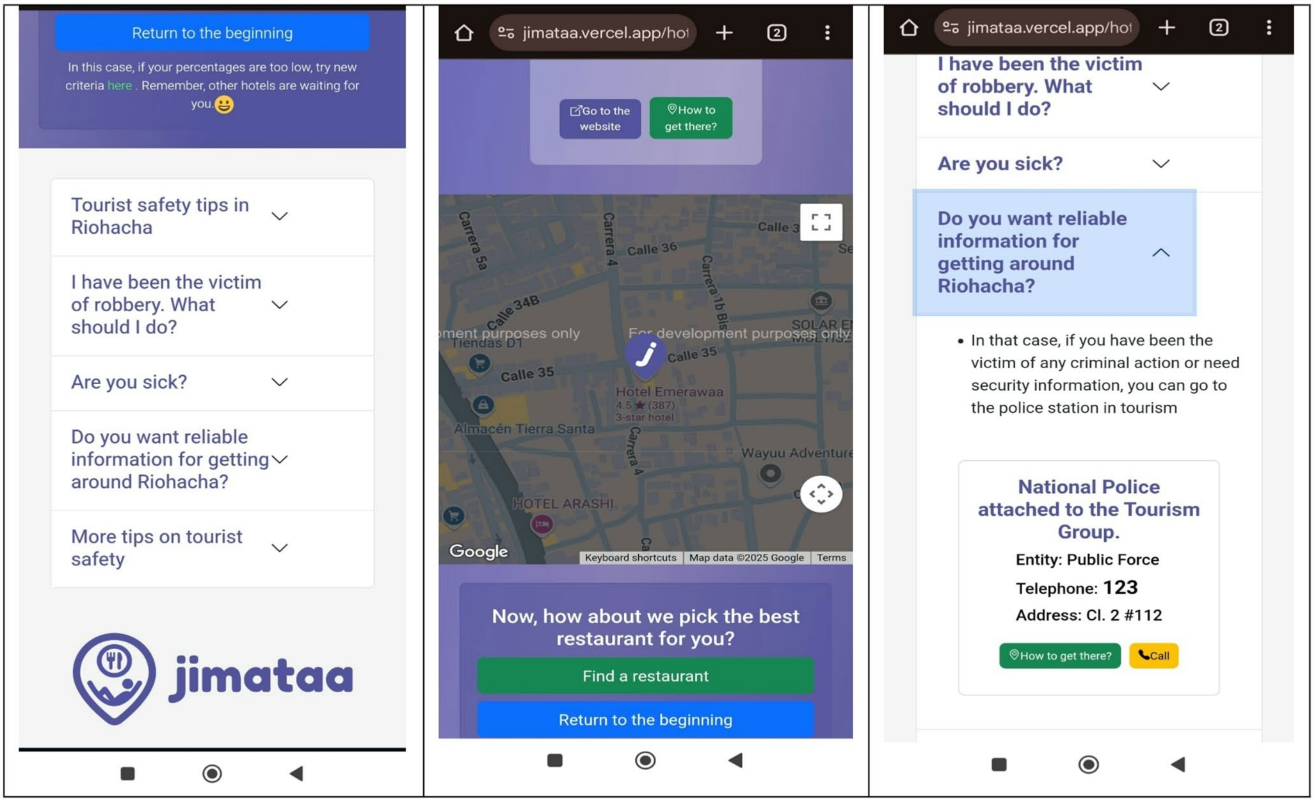

Fig. 14 Tourist security information in the mobile version of *Jimataa*

Table 5 Users who used the hotel recommender system

Criteria	Criteria and attributes	User 1	User 2	User 3	User 4	User 5
General Criteria	11 Context	0,2	0,2	0,6	0,2	0,3
	12 Location	0,3	0,3	0,2	0,3	0,2
	13 Category	0,0	0,3	0,1	0,2	0,3
	14 Visitor score	0,5	0,2	0,2	0,3	0,2
Elementary attributes	112 Acceptance of credit card payment [Y/N]	O	O	O	O	O
	113 Availability of security cameras [Y/N]	O	M	O	M	O
	113 Availability of security cameras [Y/N]	O	M	M	M	O
	114 Availability of breakfast service [Y/N]	M	M	M	M	M
	115 Availability of communication in English [Y/N]	O	O	M	O	M
	121 Distance to Beach [Meters]	Medium	Medium	Near	Near	Near
	122 Distance to City Historical area [Meters]	Far	Medium	Near	Medium	Medium
	122 Distance to City Historical area [Meters]	Medium	Medium	Near	Medium	Near
	124 Distance to Medical services [Meters]	Medium	Medium	Near	Near	Medium
	13 Category [COP]	-	Medium	Economy	Medium	Expensive
	14 Visitor score [Scale 1–10]	Very good	I don't care	Excellent	Excellent	Very good

Abreviations: O: Opciocional M: Mandatory

general criteria, such as context, location, category, and visitor score. The table also details the users' preferences for specific attributes, such as acceptance of credit card payments, availability of security cameras, breakfast services, and communication in English. The system evaluates these preferences to generate a harmonic mean and a penalty result, ultimately providing a context-based recommendation score for each user.

Table 5 presents the results of the aggregation operators and final calculation of the recommender system, showing the calculations for the best hotel alternative that matches the user's preferences. It shows the scores obtained by location and category, showing how user preferences influence the final hotel suitability score. For instance, User 3, who priorities proximity to the beach and historical areas, received a high suitability score for Bona Vida Apartments. The LSP method effectively combines user inputs to recommend the most suitable accommodation, as evidenced by the best-resulting hotels for each user. This method demonstrates the system's capability to tailor recommendations based on individual user preferences, thereby enhancing the hotel selection decision-making process. Table 6 lists five users who used the restaurant recommender system, showing their selected weights and interests for each criterion and attribute.

Table 6 illustrates how different users interact with a restaurant recommender system. Each user assigns weights to general criteria, such as culinary specialties, services, location, category, and customer ratings. In addition, specific attributes, such as acceptance of credit card payments, availability of delivery services, and vegetarian options, are considered. These weights and attributes were used to calculate a series of scores, including the harmonic mean and penalties, which ultimately determined the suitability of restaurants for each user. For example, User 3, who valued proximity to historic areas and the availability of vegetarian food, received a high suitability score for the Yotojoro restaurant.

Table 7 presents the results of the aggregation operators and final calculation of the recommender system, showing the calculations for the best restaurant alternative that matches the user's preferences.

Table 8 also shows how user preferences affect final restaurant suitability scores. The results were broken down by location, category, and customer score, demonstrating the system's ability to customise recommendations based on individual user preferences. For example, User 5, who prioritises culinary specialties and customer scores, scored highly for the I Wanna restaurant. This approach allows the system to provide more accurate and tailored recommendations, thereby improving the decision-making process for restaurant selection.

During implementation, tourists and users filled out a form to rate the functionality and usefulness of the system. Some results obtained from the implementation process with real users are presented in Table 9.

Table 9 presents the evaluation results for the recommendations provided by the system. The majority of users expressed high satisfaction, with 86.42% rating the recommendations as 5 or 4. This indicates that a significant proportion of users find the recommendations to be both effective and valuable. The high percentage of positive ratings suggests that the system largely meets user expectations; however, the areas of

Table 6 Results of aggregation operators and final calculation for hotel

Criteria	Criteria and attributes	User 1	User 2	User 3	User 4	User 5
CPA Context	Required attributes result	1	1	1	1	1
	Optional attribute results	0,5	0,5	1	0,5	0,67
	harmonic mean	0,86	0,86	1	0,86	0,91
	Penalty result	0,14	0,14	0	0,14	0,91
	Result Context CPA	0,17	0,17	0,62	0,2	0,09
D-**Location**	Location -Result D-	0,74	0,58	0,73	0,68	0,27
	Location -Result	0,2	0,17	0,11	0,18	0,67
A Category	User Price	0,46	0,88	0,63	0,88	0,13
	Result Price	0	0,23	0,05	0,18	0,68
A Category	User Score	0,9	1	0,84	0,82	0,2
	Score Result	0,48	0,23	0,13	0,25	0,88
CA	Hotel suitability CA	0,84	0,78	0,89	0,8	0,77
Best resulted		Hostal Playa Perdida −0,84	Hotel Gimaura −0,78	Bona Vida Apartments 0,89	Hotel La Vieja Sara Riohacha −0,8	Sashii Hostel & Boutique −0,77
Results in position 2 and 3		Hotel Emerawaa −0,84 Hostal Solsticio Guajiro -0,78	Hostal Solsticio Guajiro --0,77 Ayenda Cañaguate −0,76	Bona Vida Hotel 0,87 Hostel Laguna Salá By FSL -0,81	Bona Vida Hotel −0,79 Hostel Laguna Salá By FSL -0,76	Hostel Laguna Salá By FSL -0,74 Bona Vida Hotel- 0.72

Table 7 Users who used the restaurant recommender system

Criteria	criteria and attributes	User 1	User 2	User 3	User 4	User 5
General Criteria	**11 Food specialties**	0,2	0,3	0,2	0,3	0,2
	12 Services	0,2	0,0	0,2	0,1	0,0
	13 Location	0,2	0,4	0,0	0,3	0,3
	14 Category [COP]	0,2	0,0	0,2	0,2	0,3
	15 Customer score	0,2	0,3	0,3	0,1	0,2
Elementary atributes	**11 Food specialties**	Argentina, Latin, South American, Colombian, American, Italian, Spanish, Mediterranean, Middle Eastern, Sushi, Gastropub, Coffee, Ice cream with fruit, Fast food	Caribbean	Caribbean, Bar, Fast Food	Colombian, Caribbean, coffee	South American, Colombian, Caribbean, Coffee, Italian, Fusion, Seafood
	121 Acceptance of credit card payment	O	O	O	O	O
	122 Availability of delivery service	O	O	M	O	O
	113 Availability of vegetarians' food	O	O	O	O	O
	131 Distance to Beach	Medium	Near	Medium	Near	Medium
	132 Distance to City Historical area	Medium	Near	Far	Near	Near
	133 Distance to Pier and tourist police	Medium	Near	Medium	Near	Near
	14 Category	Medium	Medium	Medium	Costly	Economic
	15 Customer score	Very good	I don't care	Very good	Excellent	Very good

Abreviations: O: Opciocional M: Mandatory

Table 8 Results of aggregation operators and final calculation for restaurant

Criteria	criteria and attributes	User 1	User 2	User 3	User 4	User 5
FSIS	Result Specialty	0,71	0,73	0,78	0,88	1
CPA Services C+	Result Mandatory	1	1	1	1	1
	Result Optional	1	1	1	0,5	0,33
	Result Harmonic mean	1	1	1	0,86	0,8
	Result penalty	0	0	0	0,14	0,2
Location D-	Result Location LSP	0,58	0,87	0,16	0,78	0,88
Category A	Result category LSP	0,92	0,86	0,69	1	0,8
Customer Score A	Result Customer Score LSP	0,9	1	1	0,9	1
Restaurant CA	Result Final LSP	0,81	0,87	0,84	0,87	0,9
Best resulted		La Fermata Pizza Bistro- 0,81	Zeroa-0,87	La Jaus by La Trece −0,84	Restaurante Yotojoro −0,87	I Wanna −0,9
Results in position 2 and 3		Picnic Rioh- 0,8 Lima- 0,72	Restaurante Yotojoro −0,84 La Jaus by La Trece- 0,81	Zeroa −0,83 Picnic Rioh −0,72	Zeroa −0,72 La Jaus by La Trece −0,67	La Morena −0,77 Pichigüel Café −0,73

dissatisfaction identified should be addressed to further improve its performance.

Regarding the variety of recommendations, Table 9 shows that 77.78% of users rated the diversity of options with a 4 or 5, indicating very high satisfaction with the range of recommendations offered. This

Table 9 Results evaluation of recommender systems

Criteria	Correctess of the recommendation	Satisfaction in variety	Ease of data entry	Recommend the system to others	Secure recommendation
User evaluation and validation (Scale 1–5) (1 = Not fulfilled and 5 = Fulfilled)	5: 45,68% 4: 40,74% 3: 12,35% 2:1,23% 1:0%	5: 43,21% 4: 34,57% 3: 19,75% 2: 1,23% 1: 1,23%	5: 70,37% 4: 20,99% 3: 7,41% 2: 0% 1: 1,23%	5: 67,90% 4: 22,22% 3: 7,41% 2: 2,47% 1: 0%	Yes: 95,06% No: 4,94%

suggests that, while the majority find the variety adequate, there is still room to enrich the offering and better tailor it to the tastes and needs of all users. This makes sense, as the hotels and restaurants are adjusted to the individual preferences of each customer.

The analysis of user experience during the data entry process, presented in Table 9, shows that 91.36% of users gave a maximum rating of 4 or 5. This high percentage reflects significant satisfaction with both the data entry process and the relevance of the recommendations generated. This level of satisfaction highlights the effectiveness of the system, suggesting a high likelihood that users would recommend the platform to their friends or family.

Finally, in relation to the security of the recommendations, Table 9 shows that 95.06% of users confirmed that the web platform provided them with safe recommendations for their visit to the District of Riohacha. The high percentage of positive perceptions of security highlights the reliability of the system for providing accurate and safe recommendations. The low proportion of users with safety concerns provides an opportunity to review and strengthen aspects related to the security of the recommendations.

5 Discussion

Development and innovation in tourism Web-based recommender systems are becoming increasingly relevant in industries with constantly changing and growing user expectations [1]. As technology advances, so does the data processing techniques [3]. Incorporating these innovative methods in the tourism Web applications not only promises a significant improvement in the personalisation of recommendations, but also offers an opportunity to optimise the user experience by tailoring products and services to individual preferences.

In addition, adopting such AI-based technologies can be especially beneficial for emerging tourism destinations seeking to attract and retain visitors. The application of multi-criteria logic-based models not only improves the accuracy of recommendations, but also facilitates the management of complex visitor expectations [13]. This kind of solutions enable emerging tourism destinations to undertake their transition to smart destinations, allowing them to incorporate added value by means of easily accessible platforms such as Web systems and mobile [11, 35]. These systems allow destinations to better anticipate travellers' preferences and optimise the planning and organisation of their services. This not only optimises tourist satisfaction, but also improves the competitiveness of the sector, because an increase in the user's satisfaction is directly related to the attraction of other travellers [13].

In tourism recommender systems, there is a clear predominance of ML techniques and MCDA methods, which are primarily applied to mobile and web interfaces. The most common approaches include collaborative filtering, and reviews analysis [36, 37]. These methodologies have proven to be highly effective by analysing user behaviour patterns and specific characteristics [38]. However, there is a lack of solutions for emerging destinations that do not have still a large volume of data to scrap. The solution proposed in this paper shows that content-based models can also provide excellent recommendations, tailored to the user's expectations, by means of the use of appropriate suitability functions and logic-based aggregation models. This approach is also less time and data consuming, as it does not require to continuously collect, store and analyse large volumes of data.

The absence of methods as the LSP in current recommender systems highlights a significant gap in the field [15]. The incorporation of LSP could offer substantial improvements in preference modelling by providing a structured evaluation framework that allows for more sophisticated integration of user preferences into the recommendation process. This approach has the potential to enhance the ability of systems to reflect on and adapt recommendations to the complex and personalised preferences of users. Consequently, the integration of LSP presents a promising opportunity for innovation in the design and development of recommender systems within the tourism sector, suggesting a valuable direction for future research and advancements in this area.

User evaluation has provided clear insights into the effectiveness and acceptability of Web multi-criteria recommender systems using LSP. The results of the evaluation of the recommender system revealed a high level of overall satisfaction, highlighting the effectiveness of the Web application in offering a wide and relevant range of options. Users have shown remarkable appreciation for the variety of recommendations offered, indicating that the system meets its objective of adapting to diverse interests and preferences. The application of LSP in the design of the system has allowed for precise customisation and efficient integration of multiple criteria in the recommendation process, which significantly improves the appropriateness of the suggestions offered.

Furthermore, the facility of the Web interface with which users can enter data and use the system is well received, denoting an intuitive and efficient user experience. The predefined suitability functions have facilitated a more accessible interface, reducing complexity in the data entry process and contributing to a smoother interaction with the platform. The high rate of users willing to recommend the system and the overall perception of security and reliability reinforces confidence in the platform. This demonstrates that, in addition to providing AI-based quality recommendations, the system has managed to build a solid reputation in terms of security and reliability thanks to its ability to perform complex reasoning and adjust to specific contexts.

6 Conclusions and future work

This paper has presented the design and construction of the *Jimataa* web recommender application. The system development has been explained, including data collection, modelling of user requirements, calculation of recommendations using the LSP, and design of the user interface of gathering of user's data and presentation of results. The integration of these layers enables the delivery of relevant recommendations, significantly optimising user experience in the selection of hotels and restaurants in a tourist destination.

The implementation of the LSP method in the recommender system significantly improves the relevance and accuracy of suggestions, providing a more satisfying and personalised user experience. The implementation of AI logic operators has proven to be a powerful tool for improving the accuracy and relevance of recommendations and setting high standards for similar recommender systems in the future.

The evaluation results suggest that the recommender system based on multiple criteria and logic scoring operators offers a robust performance in terms of personalisation, ease of use, and perceived security. The interface and results of the web recommender system reflect a high level of user satisfaction. In terms of the range of recommendations, 86.42% of the users rated the system positively when adding scores of 4 and 5. Similarly, the ease of data entry received a combined rating of 77.78% for these scores, indicating a favourable response from users. These results underline that the system not only provides relevant recommendations, but also facilitates a simple and efficient data entry process.

The web recommender system has shown a high level of user interest in tourism security, with an outstanding 95.06% of users confirming that the recommendations offered were safe for their visit to the District of Riohacha. This result shows the importance of the system in improving the user experience by providing safe options, which contributes significantly to safety and security during visits to the destination. This is a main goal in some emerging destinations like Riohacha in Colombia. Trustful technological solutions that also incorporate safety indications are necessary to start the way to become a smart tourist destination.

The development of smart tourism destinations involves harnessing information and communication technologies (ICTs), where the focus is on data to make decisions that help promote sustainable tourism practices, reduce environmental impact and support local communities. The presented Web tool, *Jimataa*, is an example of this kind of technological products that are needed in smart destinations.

As future work, the multi-criteria hierarchical model proposed permits to easily extend the features used for the recommendation. It would be interesting to study the inclusion of context-aware data, such as real-time user location, or weather conditions, or the inclusion of criteria related to sustainability to minimize the impact of tourism in both the environment and the local people's activities. Furthermore, another key aspect is the maintenance of the data about the restaurants and hotels available in the touristic destination. In this line, it would be interesting to build a web tool where the service providers could update the information of their business (e.g. list of dishes, opening times, security tips, etc.), as well as a module for easily adding or removing items, with the aim of having updated information always.

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Data availability The data used in this study is available as additional supporting file in csv format.
https://doi.org/10.5281/zenodo.15169914 (accessed on 7 April 2025) [32].
https://doi.org/10.5281/zenodo.15169985 (accessed on 7 April 2025) [33].
Declarations.
Conflict of interest.
Authors declare no competing interests.

Declarations

Ethical approval The Ethics Committee for Research and Innovation (CERI) of the Rovira i Virgili University (URI).

Human ethics and consent to participate Not applicable.

Informed consent All participants in this study have given their written informed consent, in accordance with the ethical principles established by the Universitat Rovira i Virgili and the University de La Costa. Participation was completely voluntary, and participants were informed about the purpose of the study and their right to withdraw at any time without consequences.

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