User Experience in Sustainable Tourism: Enhancing Transparency in Tour Guide App Recommendations

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Abstract

This work introduces a prototype of a user-centered mobile tourism recommender system that integrates a simplified Multi-Criteria Decision Making (MCDM) method with an LLM-based natural language explanation interface to enhance the usability and transparency of sustainable tourism planning. The system allows users to weight four sustainability-related criteria – crowd levels, weather, air quality, and distance. The Borda count method is used to compute final rankings and recommendations based on real-time and simulated data and a built-in assistant, powered by OpenAI's GPT-3.5 model, explains recommendations through natural language interaction. A user study (N=13) using the System Usability Scale (SUS) and open-ended questions to reveal satisfactory usability, appreciation for the interactive interface, and perceived transparency of the system. Limitations are also discussed, including the lack of contextual guidance during initial criteria weighting and the assistant's vulnerability to off-topic queries, underscoring the need for improved prompt design and more structured user interaction.

CCS Concepts

• **Human-centered computing → Usability testing**; **User interface design**; **Empirical studies in visualization**.

Keywords

explainability, LLM, MCDM, sustainable tourism, user experience

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1 Introduction

Sustainable tourism is promoted through various strategies and practices that aim to minimize the negative impacts of tourism (e.g., environmental degradation, overtourism, economic disparities) while maximizing its benefits for local communities and the environment (e.g., economic growth, cultural preservation)[2, 27]. Given these issues, decision-makers are often faced with complex scenarios in which multiple conflicting criteria must be balanced to ensure sustainable outcomes. Multi-Criteria Decision Making (MCDM) frameworks have been widely applied in sustainable tourism planning, allowing stakeholders to evaluate alternatives according to a range of environmental, social and economic criteria [3, 9, 16]. However, traditional MCDM approaches often lack transparency, limiting their adoption by non-expert users and reducing stakeholder trust. Artificial intelligence (AI) and large language models (LLMs) offer promising tools to address this limitation by making complex algorithmic decisions more understandable and interpretable to diverse audiences [14, 26].

This work introduces a prototype of a sustainable tourism recommender system that integrates MCDM with an LLM-based natural language explanation interface to enhance the usability and transparency of sustainable tourism planning. Designed with a focus on user experience, the application allows travelers to intuitively express their personal priorities via a lightweight, preference-driven interface. Recommendations are generated in real time and visually presented on an interactive map, with clear explanations of how user input influences each ranking. To further improve interpretability and trust, the system features a built-in LLM-based conversational assistant, enabling users to ask questions and receive natural language explanations about the ranking logic and why specific destinations are recommended over others. The goal of this preliminary work is to explore the importance of user interface (UI) design in shaping transparent, AI-assisted decision support systems for sustainable tourism, highlighting how intuitive interaction and visual clarity can enhance user experience (UX) and trust.

2 Background

MCDM models are widely used in sustainable tourism to balance environmental, economic, and social goals. Studies such as Manumpil et al. [18] highlight their effectiveness in planning across regions, especially in Asia and Europe. Various approaches, such as AHP [1], fuzzy TOPSIS [10], BWM-DEMATEL [32], and SAW [24], demonstrate how MCDM enhances decision-making by handling complexity, uncertainty, and stakeholder input. Wu [31] further shows that integrating multiple MCDM methods improves reliability in evaluating tourism competitiveness. LLMs are increasingly used to make complex systems more accessible through natural language interfaces. Šturm et al. [28] used them to explain cognitive digital twins, while Nam et al. [21] applied them in IDEs to clarify code. In healthcare, Zhang et al. [33] enabled intuitive interaction with radiology systems via an LLM chat interface. Mansourian and Oucheikh [17] applied a similar approach to simplify geospatial analysis, and

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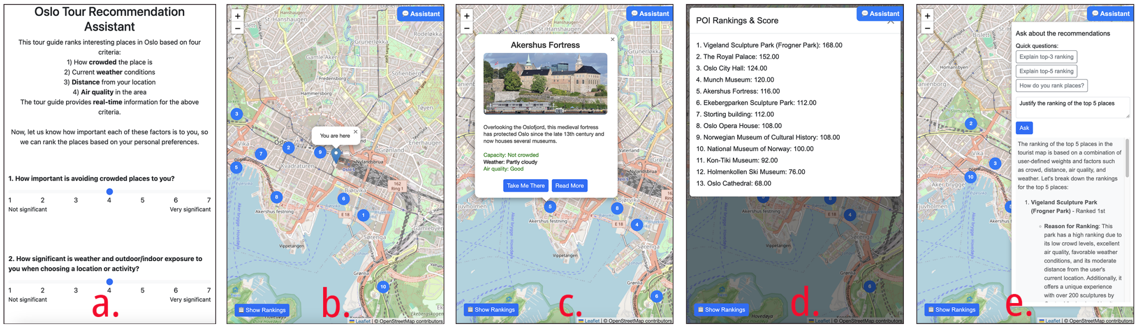

Figure 1: Screenshots of the Sustainable Tourism Recommender application (available at https://hcilab.no/rankedtour/).

Pang et al. [23] showed how LLMs can explain machine learning outputs in natural language.

However, a notable gap remains at the intersection of MCDM, LLM-based explainability, and UI design in sustainable tourism. This gap is particularly relevant for sustainable tourism, where success depends not only on technical precision but also on the willingness of travelers to adopt and act on recommendations. This work builds on the previous work of Chasanidou et al. [8] and draws inspiration from the elements mentioned above, such as the SAW and Borda count techniques [24, 31] and the use of LLMs to explain complex reasoning [19, 35]. It contributes to this emerging intersection by emphasizing how users perceive, interact with, and understand recommendation outputs in real-time travel contexts. Researchers and practitioners of the field can build on this approach to explore how explainability and UI design affect trust, comprehension, and behavior in complex decision systems, using this prototype as a foundation for creating more interpretable, context-aware, and user-centric tools that align sustainability objectives with intuitive and engaging interfaces.

3 Sustainable Tourism Recommender application

A prototype of a sustainable tourism recommender system was developed in the form of a mobile tourism guide application tailored to the city of Oslo, Norway. This prototype served as a proof-of-concept to empirically assess the feasibility of integrating explainable MCDM models into sustainable tourism planning, at a user-interface level. A simplified MCDM model, based on sustainable tourism criteria, was integrated into the recommender application to evaluate and rank attractions. The application dynamically recommends 13 points of interest (POIs) to visitors by factoring in user-defined weights, real-time contextual data, and employing the Borda count method for ranking. A web-based version of the application is available at https://hcilab.no/rankedtour/, where the GPS functionality is disabled and a static location is used for demonstration purposes.

3.1 User-defined criteria weighting

Upon initiation of their journey, users are asked to assign personalized weights, through four Likert scale questions (Fig. 1a and accessible at https://hcilab.no/rankedtour/), reflecting the significance they assign in their journeys towards specific decision criteria: real-time crowd capacity at the location, weather conditions, proximity (distance) and local air quality.

3.2 Decision criteria

3.2.1 Crowd capacity: Crowd capacity refers to the maximum number of people that a specific POI can safely and comfortably accommodate at a given time without causing overcrowding / overtourism, negatively impacting the visitor experience, or damaging the environment. In this implementation, real-time crowd-capacity information is simulated using representative mock data to illustrate the concept. Formula 1 of Table 1 illustrates the calculation of the crowd capacity.

3.2.2 Weather: Favorable weather conditions can enhance the overall visitor experience, while adverse conditions can deter visitation or affect safety. In this implementation, real-time weather data is retrieved from the API of the Norwegian Meteorological Institute (MET.no), which provides qualitative weather characterizations such as *clearsky*, *cloudy*, *rain*, and *thunderstorm*. These qualitative descriptions are mapped to a simplified numerical weather score (W) ranging from 10 (ideal, e.g., *clearsky*) to -10 (severe, e.g., *thunderstorm*). The weather's contribution to the recommendation score is moderated by an exposure factor (EXP) that accounts for the physical nature of the site (indoor vs. outdoor), reflecting its sensitivity to environmental conditions. Formula 2 of Table 1 demonstrates how the weather is calculated.

3.2.3 Distance: Distance (formula 3 of Table 1) is a key determinant in visitor decision making, often influencing the accessibility and convenience of visiting a particular point of interest (POI). In this implementation, distance refers to the straight-line (Euclidean) distance between the user's current geographic location and each POI. The distance D is expressed in kilometers and is calculated using a simplified geospatial method derived from the Haversine formula, which estimates the shortest path over the earth's surface between two points.

3.2.4 Air quality: Air quality significantly influences sustainable tourism experiences, especially outdoor activities. In this implementation, real-time air quality data is retrieved directly from MET.no API, using pollutant concentrations to calculate a normalized Air Quality Index AQI. The AQI is derived via MET.no's published

Table 1: Summary of scoring formulas used in the MCDM model.

NO.	FORMULA	PARAMETERS
1	Crowd = $(C_{\text{limit}} - C_{\text{now}})/C_{\text{limit}}$	C_{limit} is the max visitor capacity; C_{now} is the current number of visitors at a POI.
2	Weather = $W \cdot EXP$	W is the real-time weather weight; EXP is the exposure coefficient (1.0 for outdoor, 0.5 for indoor).
3	Distance = D	Distance negatively affects recommendation: higher values reduce scores.
4	Air = AQI	Higher AQI reduces scores.
5	$S_{\text{criterion}} = (n+1) - R_{\text{criterion}}$	n is the number of POIs (13); R is the raw rank for a criterion.
6	$TS = Q_1 \cdot S_{\text{crowd}} + Q_2 \cdot S_{\text{weather}} + Q_3 \cdot S_{\text{distance}} + Q_4 \cdot S_{\text{air}}$	Q_1-Q_4 are user-provided Likert weights from the four questions of Section 3.1.

formula, which transforms raw concentration values into a scale ranging from 1.0 (very good) to 4.999 (very poor), capped at 5.0 for severe pollution events (formula 4 of Table 1).

3.3 Borda method

Following data retrieval and user weight input, the prototype employs the Borda count ranking method – a robust multi-criteria decision-making algorithm – to consolidate the various criteria into a unified ranking. Specifically, the Borda scoring method assigns rankings to the 13 predefined POIs, aggregating the user's weighted preferences and the criteria-related data into an interpretable ordered list of recommendations. For each criterion (that is, crowd, weather, distance, air quality) of Section 3.2, each POI receives a ranking compared to the other POIs. Then, this ranking number R (e.g., 3 for the third-best ranked POI on Distance) is used to calculate the POI rank-based score S. Naturally, higher ranks correspond to higher scores (formula 5 of Table 1). After computing POI scores on the four decision criteria, the final weighted total score (TS) for each POI was derived using user-defined weights that reflect personal preferences at the beginning of their journey (Section 3.1). POIs are subsequently sorted based on their total aggregated score TS (formula 6 of Table 1), generating a personalized and contextually relevant ranked recommendation list displayed on the application's interactive map interface.

3.4 Development & user interface

The application was developed as a web-based platform utilizing the Bootstrap framework for mobile responsiveness and the Leaflet.js library for interactive map functionality. All POI data – including static information, aggregated real-time API data, and user-defined weights – are compiled and served as a GeoJSON response once the user submits their input. The main user interface (Fig. 1b) features an interactive map that displays the final ranked list of recommended POIs. The recommended locations are represented as blue markers, each labeled with its ranking number. Upon tapping a POI, a detailed information panel appears (Fig. 1c), presenting: (i) the POI's name and brief description, (ii) qualitative indicators for crowd capacity, weather, and air quality, and (iii) two action buttons – one for navigation via Google Maps, and another for accessing the corresponding Wikipedia article. A dedicated button in the lower left corner of the map opens a modal window displaying the complete ranking list of POIs, along with their total recommendation scores (Fig. 1d). This allows users to compare score differences and make more informed decisions when planning their visit.

A conversational assistant, implemented using OpenAI's Chat Completion API (gpt-3.5-turbo), is integrated into the interface via a button in the upper right corner (Fig. 1e). This approach was chosen for its simplicity, predictability and control, ensuring that each explanation remains tightly aligned with the underlying MCDM output. For each interaction, only a minimal message structure is sent to the API, consisting of a static system prompt[1]. In addition to supporting free-text user queries on the rankings, the assistant interface includes three predefined input options[2], which are presented as clickable buttons in the UI to reduce cognitive and physical effort for users, particularly in this mobile context. The system and user prompts were designed and refined iteratively by two authors to ensure clarity, consistency, and alignment with the assistant's explanatory role.

This prototype is designed as a proof-of-concept to explore transparency and interpretability in sustainable tourism recommendation systems, rather than to offer fully accurate or exhaustive recommendations. Consequently, several limitations are acknowledged. The underlying MCDM formula is deliberately simplified and, as such, may not always produce fair or balanced rankings. Distance calculations are based on Euclidean (straight-line) measures, which do not account for actual travel paths or road networks, potentially underestimating true accessibility. Moreover, the real-time crowd data used in the model are simulated mock values intended to illustrate the concept, rather than reflect actual visitor counts. Currently, many relevant decision-making criteria, such as opening hours, live traffic conditions, and personalized visitor preferences, are not included. These simplifications are intentional: the system prioritizes user interface design and the exploration of explainable decision-making processes over content precision. As such, the model serves as a testbed for evaluating how users perceive and interact with transparent recommendation output, rather than providing definitive travel guidance.

4 User study

To evaluate the Sustainable Tourism Recommender application, a user study was conducted in which participants were provided with a web link to the application and asked to role-play a scenario where they were located at Oslo Central Station and intended to visit various points of interest (POIs) in the city. For consistency and control, the GPS functionality was disabled and replaced with a static geolocation fixed at Oslo Central Station. Participants

[1]System prompt: *"You are a helpful assistant that explains a list of ranked points of interest (POIs) in a tourist map. Use the following JSON array of ranked POIs to explain why some are ranked higher than others: [JSON array]. Explain the rankings based on user-defined weights and factors like crowd, distance, air quality, and weather. Do not mention the raw scores unless you are asked to. For crowd, air quality, and weather, values are aggregated from real-time data and they are real-time values."*.

[2]Predefined user prompts: *"Justify the ranking of the top 3 places", "Justify the ranking of the top 5 places", "What is the formula you use to rank places?"*.

Table 2: Thematic summary of open-ended user feedback.

CATEGORY	COMMON THEMES & OBSERVATIONS
General experience	- App is described as "easy to use" and "straightforward". - Helpful for newcomers to quickly understand POIs.
Most useful features	- Integration of real-time, contextual data was appreciated. - Map and location awareness feature frequently cited. - Preference input before recommendations seen positively.
Confusing or difficult features	- Preference survey appears suddenly and lacks context. - Ranking scores in the modal box do not mean much unless the Assistant is used for explaining. - Assistant lacks memory of previous exchanges and struggles with free-text queries that are not about the ranking.
Interaction with Assistant	- Assistant seen as helpful to interpret ranking and scores. - Assistant lacks memory of previous exchanges and struggles with free-text queries that are not about the ranking.
Suggestions for improvement	- Improve Assistant memory and prompt handling. - Add more detailed POI info (not just Wikipedia). - Clarify purpose of preference survey (user-defined weights). - Add the rankings and formula explanation in a dedicated screen, before the map screen, and use the Assistant on map if need revisiting. - Add more decision criteria, like opening hours et al.
Influence on travel	- Increased awareness of air quality and weather in travel planning. - Helped users prioritize top POIs based on preferences. - Some skepticism about whether sustainability-related criteria, like crowd capacity and air quality, could affect travel behavior significantly.

were asked to explore the application on their smartphones for approximately 15–20 minutes. To protect participant anonymity, no user prompts and no additional activities – such as IP addresses – were stored or logged during the study. Following this exploration phase, participants were invited to complete a structured questionnaire designed to assess perceived usability, overall user experience, and to gather qualitative insights into the transparency and interpretability of the recommendations. The questionnaire consisted of three main components. First, demographic questions about age group and gender were asked. Then, to measure perceived usability, the 10-item System Usability Scale (SUS) questionnaire [6] was used. SUS is an instrument that allows usability practitioners and researchers to measure the subjective usability of products and services. Specifically, it is a 10-item questionnaire that can be administered quickly and easily and returns scores ranging from 0–100. SUS scores can also be translated into adjective ratings and grade scales [4]. SUS has been shown to be a reliable and valid instrument, robust with a small number of participants, and to have the distinct advantage of being technology agnostic, which means it can be used to evaluate a wide range of hardware and software systems [5, 6, 13, 29]. Finally, six open-ended questions were asked[3]. These open questions aimed to gather detailed feedback on user experience, useful features, confusing or challenging UI aspects, interaction with the integrated LLM-based assistant, suggestions for improvement and how the application might influence participants' travel planning decisions. The open-ended survey questions were developed by the author team and were crafted based on the team's domain expertise, previous work [8] and iterative review to ensure relevance, clarity, and openness to user perspectives. The questionnaire was fully anonymized and implemented using the LimeSurvey.org Community Edition platform.

[3]Open-ended questions: *"How would you describe your overall experience with the Tour Guide?", "Which feature/s did you find most useful?", "Which feature/s did you find confusing or difficult to use?", "How would you describe your interaction with the "Assistant" option?", "What improvements or changes would you suggest to enhance your experience with the Tour Guide?", "Do you believe this Tour Guide would influence your awareness or behavior during your travels? Please explain.".*

The study was subject to certain limitations, including a relatively small sample size; however, based on established practices in related research [7, 15, 22, 29] from which the study design was derived, the sample was considered adequate to obtain valid observations and generate meaningful user feedback. Questions regarding participants' prior technology experience were omitted to minimize survey fatigue and prevent potential priming effects, as the study aimed to evaluate general usability across a broad user population without assuming prior technical expertise.

4.1 Results

A total of 13 participants participated in the evaluation study. Demographically, seven participants were 25–34 years old, five 35–44 years old, and one participant was 45–54 years old. The gender distribution included seven female and six male respondents. The average SUS score was 80.58 (SD = 8.61), indicating a satisfactory level of usability overall, achieving a bordeline SUS "B" grade and a "Good" rating. To explore user perceptions of transparency, interpretability, and interaction design in more depth, a qualitative analysis was conducted on open-ended feedback. The responses were thematically coded independently by two authors into major thematic categories, following the categories of the six open-ended questions described in Section 4. Coding was refined through discussion until full interrater agreement was reached, and the resulting themes are summarized in Table 2.

5 Conclusion

This preliminary work represents a constructive first step towards exploring the integration of an MCDM method with an LLM-based natural language explanation interface for sustainable tourism planning. An initial implementation was used to allow users to engage freely with the system and to surface interaction gaps through natural use. Despite the simplicity and limitations of the approach due to its early stage status, valuable insights were obtained regarding user interface design considerations, the interpretability of LLM-generated explanations, and the role of such systems in supporting preference-driven tourism planning.

The evaluation study highlighted several important insights on user interaction with the Sustainable Tourism Recommender application. With an average SUS score of 80.58, users generally perceived the system as user-friendly, intuitive, and valuable to improve decision making during travel planning. The integration of real-time contextual data, particularly regarding crowd capacity, weather conditions, and air quality, was highly valued, aligning with previous literature that emphasizes the role of real-time information in sustainable tourism practices [2, 30]. In addition, the transparency of the rankings was considered enhanced by interactions with the conversational assistant, underscoring the need for improved integration between explanatory interfaces and the core recommendation functionality.

The most prominent challenge identified was related to the initial user-defined criteria weighting, which lacked adequate context or explanatory content. This issue reflects the inherent complexity in effectively communicating multi-criteria decision-making processes to end-users and, at the initial stage, richer textual descriptions and example-driven visual aids could mitigate this issue [20, 25]. Another challenge was that free-text queries not related to the topic of rankings were shown to degrade the perceived performance of the assistant, specifically designed to explain ranking outputs and formulas. This outcome is consistent with previous findings showing that vague or multitask prompts, especially those outside the LLM's intended context, reduce reliability and increase hallucinations [11, 12, 34]. To mitigate this issue, future implementations should include stronger prompt-engineering mechanisms to constrain user input to the intended task and guide interactions more effectively. Participants also expressed skepticism about whether sustainability-related criteria, notably crowd capacity and air quality, would meaningfully influence their travel behaviors. This indicates a potential gap between users' expressed preferences and actual behavioral outcomes, a common challenge in promoting sustainable tourism practices [27].

In addition to the aforementioned actions, future work should focus on refining the model's accuracy by integrating realistic route and transportation data, live visitor metrics, and additional decision criteria such as reviews, opening hours, event schedules, or pricing. Furthermore, longitudinal studies could investigate how sustained interactions with LLM-based explanation interfaces could genuinely shift user behaviors toward sustainable tourism practices, providing valuable insights for policymakers, planners, and tourism stakeholders.

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