

HikeSmart: A Personalized AI Assistant for Multi-Facet Hiking Preparation and Risk

Tikno*, Anggit Mulianing Pambudi, Citra Maulidya Haritsah, Dinar Putra Mubarak and Adinda Dwi Nur Rahmawati

Received: 18 April 2026
Accepted: 6 September 2026
Published: 30 September 2026

Keywords:

*Recommendation
Systems, Mountain
Hiking, Personalization,
Risk Mitigation, Human-
Computer Interaction
(HCI).*

ABSTRACT

Mountain hiking's growing popularity was paralleled by persistent safety risks, often stemming from inadequate preparation and the limitations of one-size-fits-all planning tools. Existing solutions typically failed to provide guidance tailored to a user's specific experience level and the dynamic context of an expedition. To address this gap, this paper proposed and evaluated HikeSmart, a personalized AI assistant for hiking preparation. The system's core technical contribution was an integrated decision-support engine governed by a multi-persona framework (novice, experienced, group leader). This engine combined a heuristic scoring algorithm for personalized route recommendation with a rule-based inference engine for generating dynamic, context-aware logistics checklists. A usability study with 15 participants yielded a high mean System Usability Scale (SUS) score of 85.5, placing it in the 'excellent' usability category. Qualitative feedback confirmed that this personalized and integrated approach improved user confidence during the planning phase.

INTRODUCTION

Mountain hiking has experienced remarkable growth in Indonesia, with the country's approximately 400 mountains attracting around 3 million visitors in 2023 [1]. This resurgence reflects a broader global trend toward outdoor recreation and underscores its increasing social and economic significance. However, this popularity is accompanied by persistent and serious safety risks. Between 2013 and 2024, Indonesian mountain trails recorded 155 fatalities, with the primary causes being inadequate preparation, prolonged weather exposure, and navigational errors [2]. Despite regulatory interventions such as the SNI 8748:2019 safety standard and visitor quotas, preventable incidents continue to occur at an alarming rate.

The core problem is a fundamental deficit in individualized, intelligent decision-support during the pre-hike planning phase. Current digital solutions are inadequate for mitigating these risks. Commercial platforms such as AllTrails and Komoot function primarily as passive trail databases; while comprehensive in coverage, they lack proactive risk assessment and dynamic logistics planning. They offer no mechanism to tailor guidance to a specific user's experience level or to dynamically respond to transient environmental conditions. Consequently, the entire cognitive burden of risk assessment falls on the user, who must manually consolidate information from multiple, fragmented sources—a challenge that is most acute for novice hikers who are least equipped to perform such synthesis.

To contextualize this gap, three closely related research domains are surveyed. In the domain of recommendation systems, such systems are widely used in sports to enhance performance through personalized suggestions for training and diet [3], [4], employing techniques like hybrid collaborative filtering and content-based machine learning [5], [6]. However, their focus on preference-matching and performance optimization is insufficient for the high-stakes safety requirements of mountain hiking, which demands risk mitigation extending beyond simple

preference-based recommendations. Regarding AI for outdoor safety, research has primarily focused on injury prediction using machine learning [7], [8], [9] and environmental risk assessment for hazards such as extreme heat or air pollution [10], [11]. While this work makes invisible physiological and environmental risks more manageable, it provides generalized safety insights that are not integrated with an individual hiker's capabilities or the specific context of a planned expedition. In the domain of context-aware user modeling, Context-Aware Systems (CAS) leverage dynamic user data—such as location, activity, and skill level—to anticipate needs and deliver proactive, relevant services [12], [13], [14]. The proven success of CAS in domains such as healthcare and education [15], [16] provides a robust foundation for modeling the complex, evolving context of a hiking trip, where factors such as weather and user fatigue are critical.

The literature reveals a critical gap at the intersection of these domains. While commercial applications excel at trail discovery, their personalization is limited to static difficulty tags, failing to account for the dynamic interplay between a user's individual capabilities, a route's specific hazards, and transient environmental conditions. Academic research, while advancing each sub-domain in isolation, has yet to produce an integrated, end-to-end decision-support system. Specifically, there is a notable absence of risk-aware recommender systems in the recreational domain that dynamically synthesize user vulnerability with environmental threats to provide actionable, personalized safety guidance. This gap represents both a safety problem and a Human-Computer Interaction (HCI) challenge that no existing tool has addressed.

To fill this void, this paper introduces HikeSmart, a personalized AI assistant for hiking preparation and risk mitigation. The core motivation is to shift the planning paradigm from passive information retrieval to guided, data-driven decision support—making expert-level preparation accessible to hikers of all experience levels by placing intelligent, context-aware guidance directly in their hands before they reach the trailhead.

The primary aims of this work are: (1) to design a multi-persona user model that captures the distinct planning needs of novice, experienced, and group leader hikers; (2) to develop a transparent, rule-governed AI engine that generates both personalized route recommendations and dynamic logistics checklists; and (3) to empirically validate the system's usability and effectiveness through a structured user study.

The primary contributions and significance of this paper are threefold. First, this study designs and implements a novel heuristic scoring algorithm that dynamically weights safety, user-to-route compatibility, and real-time weather factors to personalize route recommendations based on the multi-persona model. Second, a forward-chaining, rule-based inference engine is developed that translates complex trip context—user persona, route attributes, and weather forecasts—into an actionable logistics checklist, moving beyond the static equipment lists found in existing tools. Third, the system is validated through a preliminary, proof-of-concept usability study (N=15), achieving a mean System Usability Scale (SUS) score of 85.5; while the small sample size limits generalizability, the result provides initial quantitative and qualitative evidence that the integrated, personalized model effectively reduces planning cognitive load and enhances hiker confidence. By treating route safety, environmental risk, and gear logistics as an interdependent whole, HikeSmart demonstrates that context-aware AI can materially improve safety preparedness in high-stakes recreational activities.

The paper is organized as follows: Section 2 details the system methods and design; Section 3 presents experimental results and discussion; and Section 4 concludes the paper.

METHODS

This section details the design, development, and evaluation of HikeSmart. The system assumptions, architecture, data sources, the AI recommendation core, implementation specifics, and evaluation procedure are delineated.

Design Assumptions

The design of HikeSmart rests on several explicit assumptions that bound the system's scope and validity. First, it is assumed that target users possess a smartphone with a stable internet connection, which is necessary for real-time weather data retrieval and map rendering. Second, it is assumed that users provide an honest self-assessment of their experience level at registration; while the system is designed to dynamically refine this classification, the initial persona assignment depends on truthful input. Third, it is assumed that the geospatial and route data sourced from OpenStreetMap and crowdsourced GPX files are sufficiently current and accurate for the regions of interest; the system does not independently verify trail conditions in real time. Fourth, it is assumed that weather forecast data from external API providers (OpenWeatherMap, BMKG) accurately reflects near-term conditions with a reasonable margin of error. Finally, for the evaluation phase, it is assumed that the 15 recruited participants are broadly representative of the three target user personas and that their responses in a controlled setting reflect genuine planning behaviors.

System Architecture

HikeSmart employs a modular, service-oriented architecture for scalability and maintainability (Fig. 1). A User Interface layer communicates with backend services via an API Gateway. The system's core intelligence is distributed across several modules: an AI Personalization Engine, Fitness & Readiness Assessment, Route & Terrain Intelligence, a Logistics Planner, a Weather & Environmental Engine, and a Collaboration & Sharing Module. These are supported by backend services for databases, authentication, and analytics.

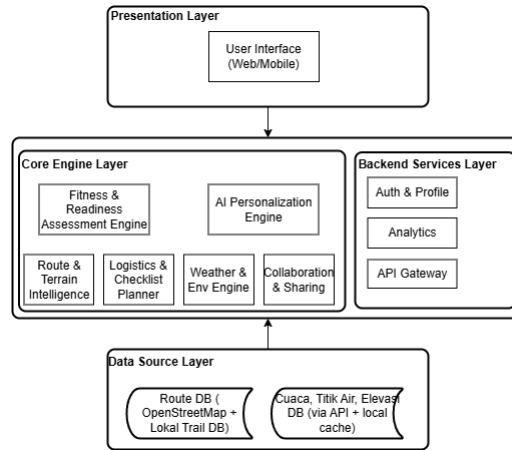


Fig. 1 HikeSmart Architecture

Data Acquisition and Representation

The system's intelligence is fueled by diverse data, acquired as follows:

Geospatial and Route Data: Hiking trail data are aggregated from public repositories (OpenStreetMap) and crowdsourced GPX files. Each trail is stored as a LINESTRING geometry in a geospatial database, enriched with attributes such as *elevation gain* and *difficulty score*. Elevation profiles are obtained using the Google Elevation API.

Contextual Data: Real-time and forecast weather data are procured via APIs from providers such as OpenWeatherMap and the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG).

User Data: Upon registration, users provide foundational data (e.g., age, biometry, experience level). The system then implicitly collects route preferences and planning history to continuously refine the user model.

Multi-Persona User Modeling

HikeSmart's key innovation is its multi-persona framework. The system classifies users into three personas—novice, experienced, or leader—to deliver tailored recommendations. The initial classification is based on self-declared experience but is designed to evolve dynamically with a user's activity history. This persona dictates the recommendation focus; for instance, novices receive safety-prioritized guidance, while experts are shown more challenging routes.

The AI-Powered Recommendation Core

For HikeSmart's decision-support core, a hybrid approach combining a heuristic algorithm with a rule-based engine was deliberately selected, rather than a purely data-driven machine learning model. This design choice is grounded in two key principles for high-stakes safety domains. First is the principle of Explainability: a hiker's safety depends on understanding why a certain route or piece of gear is recommended. The heuristic and rule-based systems provide transparent reasoning (e.g., 'this route is penalized due to forecasted high winds'), whereas 'black-box' models cannot. Second is the challenge of the Cold Start Problem: effective machine learning for safety would require vast datasets of trips correlated with specific safety outcomes, which are not publicly available. This knowledge-driven approach is effective from the first use, encoding established safety expertise into its logic.

1. **Personalized Route Recommendation:** A Heuristic Filtering and Scoring Algorithm The algorithm executes a multi-stage process.
 1. **Initial Filtering:** First, the system filters the global route database (R_{all}) to a candidate set (R_{cand}) using explicit user constraints (e.g., geographic area) and implicit persona-based constraints (e.g., excluding routes with difficulty > 6 for a 'novice').
 2. **Heuristic Scoring:** Each candidate route $R \in R_{cand}$ is assigned a score, S_R , via a weighted sum of three normalized heuristic functions:

$$S_R = w_{safety} \cdot f_{safety}(R) + w_{match} \cdot f_{match}(R, P) + w_{weather} \cdot f_{weather}(R, T) \quad (1)$$

The weights (w_{safety} , w_{match} , $w_{weather}$) are dynamically adjusted based on the user's persona (P), with $\sum w = 1$. The weights are justified as follows:

- Novice ($w_{safety}=0.6$, $w_{match}=0.3$, $w_{weather} = 0.1$) : Prioritizes risk mitigation. The high w_{safety} favors inherently safe trails, while w_{match} prevents recommending routes far beyond the user's capability.
- Experienced ($w_{safety}=0.3$, $w_{match}=0.5$, $w_{weather} = 0.2$) : Prioritizes challenge. The high w_{match} finds suitably challenging routes, while a substantial w_{safety} still accounts for objective risks.
- Group Leader ($w_{safety}=0.7$, $w_{match}=0.2$, $w_{weather} = 0.1$) : Prioritizes group safety. The dominant w_{safety} reflects responsibility for others, favoring fundamentally safe routes over individual challenge.

The functions are defined as:

- Safety Score (f_{safety}): Quantifies a route's inherent safety based on static attributes like distance between water sources (D_{avg_ws}) and shelters (D_{avg_sh}), and a penalty for historical hazards (H_{risk}), normalized to a $[0, 1]$ range.
- Match Score (f_{match}): Measures compatibility between a route's difficulty ($Difficulty_R$) and the user's experience ($Experience_P$) using a Gaussian function to reward close matches.
- Weather Score ($f_{weather}$): Assesses forecast favorability as a product of scores for temperature, precipitation, and wind.

$$f_{safety}(R) = \alpha \cdot N(D_{avg_ws}) + \beta \cdot N(D_{avg_sh}) + \gamma \cdot (1 - H_{risk}) \quad (2)$$

with $\alpha + \beta + \gamma = 1$ (set to 0.4, 0.3, and 0.3, respectively, in the current implementation). $N(\cdot)$ denotes min-max normalization to the $[0, 1]$ range; D_{avg_ws} and D_{avg_sh} are the average distances (km) from route R to the nearest water source and emergency shelter, respectively; and $H_{risk} \in [0, 1]$ is a historical-hazard penalty derived from recorded incidents associated with R. Higher water/shelter accessibility and lower historical hazard yield a higher safety score.

$$f_{match}(R, P) = \exp(-(Difficulty_R - Experience_P)^2 / (2\sigma^2)) \quad (3)$$

$Difficulty_R \in [1, 10]$ is the normalized difficulty rating of route R, $Experience_P \in [1, 10]$ is the calibrated experience level associated with persona P, and σ is a tolerance parameter controlling how sharply the score decays as difficulty diverges from the user's experience ($\sigma = 2$ in the current implementation). The Gaussian form yields a score of 1 for a perfect difficulty-experience match and decays smoothly toward 0 as the mismatch grows.

$$f_{weather}(R, T) = f_{temp}(T) \times f_{precip}(T) \times f_{wind}(T) \quad (4)$$

where each sub-score is normalized to $[0, 1]$ and derived from the trip-window forecast T using piecewise-linear penalty functions: f_{temp} penalizes deviation from a comfortable range (10–20°C); f_{precip} decreases as forecast precipitation probability increases; and f_{wind} decreases as forecast sustained wind speed increases beyond route-specific exposure thresholds. Because the three sub-scores are multiplied, an unfavorable reading on any single dimension (e.g., high wind) substantially lowers the overall weather score, reflecting the compounding nature of weather-related hazards.

3. **Ranking and Presentation:** Routes in R_{cand} are ranked by their final score S_R and presented to the user, as detailed in (1). The result is then presented to the user (Fig. 2).



Fig. 2 Personalized Route Recommendation Feature

2. **Dynamic Logistics Planning:** A Rule-Based Inference Engine A forward-chaining, rule-based inference engine generates a dynamic logistics checklist. The engine evaluates rules (see sample in Table I) against trip context facts (user persona, route attributes, weather forecast) to suggest essential and context-appropriate gear. All logistics are presented as check list for the user (Fig. 3).

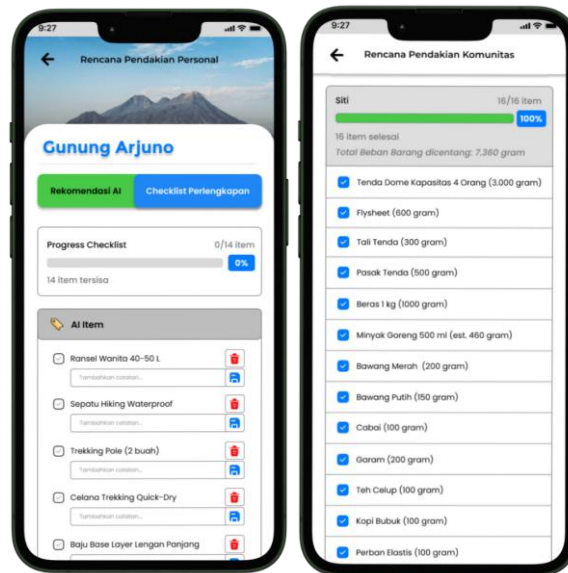


Fig. 3 Dynamic Logistics Planning Feature

Table 1. Dynamic Logistics Planning Feature

Rule ID	IF (Conditions)	THEN (Action)	Rationale
R01	persona == 'novice'	ADD_ITEM('Printed Map', 'Compass', 'Whistle')	Ensures novices have essential non-digital backups.
R02	trip_duration > 1 AND weather.min_temp < 5°C	ADD_ITEM('4-season Sleeping Bag', 'Thermal Liner')	Prevents hypothermia. Aligns with standard wilderness medicine protocols advising insulated systems for temperatures below 5°C.
R03	route.terrain_type == 'exposed_ridge' AND weather.wind_speed > 40 km/h	ADD_ITEM('Windproof Jacket', 'Goggles')	Mitigates risks from high winds on exposed terrain.
R04	route.has_water_source == false AND trip_duration > 0.5 days	ADD_ITEM('Water Filter/Purifier', 'Extra Water Bladder')	Ensures water self-sufficiency on dry routes.

R05	persona == 'group_leader'	ADD_ITEM('Group First Aid Kit', 'Satellite Messenger')	Ensures leader is equipped for group-level incidents, aligning with established best practices for outdoor leadership and duty of care.
R06	weather.precipitation_prob > 60%	ADD_ITEM('Rain Poncho', 'Waterproof Pack Cover')	Ensures gear and person stay dry.

Implementation Details

HikeSmart was implemented using Laravel (PHP) for the backend API, a MySQL/PostGIS database for data storage, and Redis for caching. The frontend is a Vue.js single-page application with Leaflet.js for geospatial visualization. External data are integrated via REST APIs from OpenWeatherMap, BMKG, and the Google Maps Platform.

Evaluation Methodology

HikeSmart was validated through a structured usability study governed by four procedural components.

1. Experimental Setup

The study was conducted in a controlled laboratory setting to minimize environmental distractions and ensure consistency across sessions. Fifteen participants were recruited through purposive sampling, stratified to match the system's three target personas: 5 novice hikers (0–2 hikes per year, no formal training), 5 experienced hikers (≥ 10 hikes per year, familiar with multi-day expeditions), and 5 group leaders (individuals who have led hiking groups on at least three occasions). Each participant completed an identical sequence of four predefined tasks designed to engage all major system features: (1) creating a user profile and declaring experience level; (2) using the personalized route recommendation engine to select a mountain for a specified trip window; (3) reviewing and interacting with the auto-generated logistics checklist; and (4) interpreting the weather and safety alert information. Sessions were moderated and lasted approximately 45–60 minutes per participant.

2. Data Collection

Two instruments were used to collect evaluation data. For quantitative measurement, participants completed the 10-item System Usability Scale (SUS) questionnaire immediately after finishing the task sequence, while the experience was still fresh. For qualitative enrichment, each session was followed by a semi-structured interview of approximately 10–15 minutes. The interview protocol covered three themes: (a) perceived strengths of the personalization features, (b) friction points or areas for improvement, and (c) comparison with any prior hiking planning tools the participant had used. Interviews were audio-recorded with participant consent and transcribed verbatim for analysis.

3. Data Analysis

Quantitative SUS responses were scored according to the standard Brooke formula [17]: odd-item scores are reduced by 1 and even-item scores are subtracted from 5; the sum of all adjusted scores is then multiplied by 2.5 to yield a final score on a 0–100 scale. Individual scores were aggregated to compute the group mean and standard deviation. Persona-level means (novice, experienced, leader) were also computed to identify differential perceptions across user groups.

Qualitative interview transcripts were analyzed using inductive thematic analysis following the six-phase framework of Braun and Clarke [18]. Two researchers independently coded the transcripts, identifying recurring themes. Codes were then discussed and merged into higher-level themes through consensus, ensuring inter-rater reliability.

4. Statistical Testing

Given the small sample size ($N=15$), descriptive statistics were applied—mean, standard deviation, and range—as the primary quantitative measure. The mean SUS score was interpreted against established population benchmarks: scores above 80.3 correspond to the top 10th percentile (“Excellent” grade), scores of 68 represent average usability, and scores below 51 indicate below-average systems [19]. No inferential statistical tests (e.g., ANOVA) were applied across persona sub-groups due to the limited sub-group size ($n=5$ per group), which would be underpowered for such comparisons. The qualitative thematic analysis served as the primary validation instrument for identifying nuanced, persona-specific usability patterns that descriptive statistics alone cannot capture.

RESULTS AND DISCUSSION

This section presents empirical findings from a usability study designed to evaluate the HikeSmart application with 15 participants representing the system's target personas (novice, experienced, leader). The group was diverse in age, hiking frequency, and leadership experience, ensuring robust validation of the system's tailored functionalities.

1. Usability Evaluation: System Usability Scale (SUS)

For quantitative evaluation, the System Usability Scale (SUS) was used. HikeSmart achieved an excellent mean SUS score of 85.5. According to established benchmarks, a score above 80.3 places a system in the top 10% for usability. This result firmly places HikeSmart in the “Excellent” category, signifying high perceived usability, learnability, and user satisfaction (Fig. 4).

Disaggregated by persona, the mean SUS scores were 87.6 (SD = 2.6) for novice hikers, 84.7 (SD = 1.2) for experienced hikers, and 84.2 (SD = 2.2) for group leaders (n = 5 per group). All three sub-groups fell within the “Good” to “Excellent” range, with the highest scores observed among novice participants, consistent with the qualitative theme that safety-prioritized personalization was most valued by less experienced hikers; the small per-group sample (n = 5) means these differences are reported descriptively and should be interpreted with caution rather than as statistically confirmed effects.

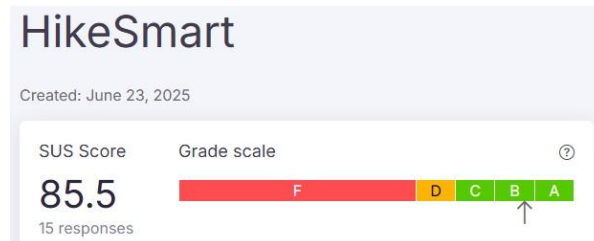


Fig. 4 SUS Score

2. Qualitative Feedback Analysis

Qualitative data collected from post-study questionnaires and interviews revealed several key themes.

- **Identified Strengths:** Users consistently praised three core aspects. The Intelligent Personalization of routes was highlighted for boosting novice confidence. The Holistic and Centralized Planning, featuring a dynamic checklist and integrated data (weather, waypoints, gear), was deemed exceptionally practical. Finally, the Enhanced Sense of Safety from features like water source locations and weather alerts was cited as a major advantage over standard mapping apps.
- **Areas for Improvement:** Participants also provided a clear roadmap for future work. Common suggestions included incorporating Community/Social Features (e.g., live tracking, trail condition forums), expanding the Route Database to more geographic regions, and adding Advanced Customization for power users (e.g., in-app GPX editing).

In summary, the excellent SUS score, combined with positive qualitative feedback, validates HikeSmart as a highly usable and effective tool for hiking preparation. The study confirms that its core AI-driven features address real-world hiker challenges and provides clear directions for future enhancements.

3. Interpretation of Principal Findings

• Causal Arguments

The high mean SUS score of 85.5 is not an isolated result; it can be causally attributed to specific design decisions. The primary driver is the multi-persona model: by adapting the interface vocabulary, route filters, and checklist content to a user’s declared experience level, the system eliminates the irrelevant information that creates cognitive overload in general-purpose tools. This reduction in extraneous cognitive load directly enables users to focus on the decision at hand, which is a well-established antecedent to high usability perception in HCI research. A secondary causal factor is the integration of previously fragmented tasks—route selection, gear planning, and weather assessment—into a single, coherent workflow. Participants who had previously managed these as separate activities on multiple platforms found the consolidation to be the most immediately measurable practical benefit, which directly elevated their satisfaction scores. Conversely, the relatively lower enthusiasm from experienced hikers compared to novices is causally linked to the current ceiling on route data: power users who already know their target peaks derive less incremental value from the recommendation engine’s filtering, as they seek customization rather than guidance.

• Speculations

Beyond the immediate findings, several broader implications can be cautiously advanced as hypotheses to be formally tested in future work. It is speculated that the strong novice response—where the safety-prioritized persona configuration was most praised—points to a latent, unmet market for proactive AI guidance in recreational safety that existing platforms have systematically underserved. If this pattern holds at larger scale, it suggests that the commercial dominance of passive, database-style applications in the outdoor sector may not reflect genuine user preference but rather the absence of a superior alternative. Furthermore, it is speculated that the demand for community and social features, voiced by the majority of participants across all persona groups, is not merely a feature request but may reflect an underlying trust mechanism: users may be more willing to rely on AI-generated safety guidance when it is

corroborated by peer experience data from the same trails. Incorporating such social validation layers could therefore amplify the safety impact of the AI core in ways that extend beyond what the current system architecture can demonstrate; both claims remain speculative and require dedicated empirical validation rather than being treated as established findings.

- ***Deductive Arguments***

From the evidence gathered, two broader conclusions can be logically deduced. First, the success of the multi-persona framework deductively supports the general thesis that safety-critical AI applications require explicit user modeling to be both usable and trustworthy. A system that applies identical reasoning to a first-time hiker and a seasoned mountaineer cannot be safe for the former or useful for the latter; this study provides an empirically grounded proof of that principle within the recreational domain. Second, the strong usability result achieved without any machine learning component—using only heuristic scoring and rule-based inference—deductively confirms that explainability and transparency are not merely desirable properties in high-stakes AI but are functionally necessary ones. The participants' ability to understand why a route or gear item was recommended was consistently cited as a confidence-building factor, logically implying that opaque models would have underperformed in this context regardless of their predictive accuracy.

- ***Comparison with Prior Work***

The findings of this study align with and extend prior research. While confirming personalization principles from sports recommender systems [4], HikeSmart applies them to proactive risk mitigation, a shift from the typical focus on performance optimization [3], [6]. Unlike standalone navigation or specialized safety apps [20], HikeSmart provides an integrated planning framework. The positive reception of its unified approach—where route difficulty, weather, and logistics are considered in concert—demonstrates the value of this integrated model and directly addresses the research gap identified in this study.

CONCLUSION

This paper designed, implemented, and validated HikeSmart, a personalized AI assistant for hiking preparation and risk mitigation. Three aims were fulfilled: a multi-persona user model classifying hikers as novice, experienced, or group leader; a transparent AI engine combining a heuristic scoring algorithm for route recommendation with a forward-chaining inference engine for logistics planning; and empirical validation through a usability study (N=15) yielding a mean SUS score of 85.5 ("Excellent"), supported by qualitative evidence of increased planning confidence. The core finding is clear: treating user experience, route hazards, and environmental conditions as interdependent rather than isolated variables allows AI-assisted planning to make high-stakes preparation accessible and safer for all hikers.

Limitations and Future Work

Several limitations define the research roadmap for this study:

1. **Generalizability:** The controlled lab setting cannot replicate real-world cognitive pressures. A longitudinal field study deploying HikeSmart to a larger, diverse cohort is the highest priority to assess real-world utility and behavioral impact.
2. **Benchmarking:** User satisfaction was demonstrated, but recommendation quality was not measured against an expert standard. A formal validation study will compare HikeSmart's outputs against certified mountain guides across predefined scenarios to quantify safety and added value.
3. **Real-World Safety Impact:** Perceived confidence was measured, not actual safety outcomes. A long-term observational study—conducted with user consent and authority partnerships—will investigate whether HikeSmart adoption correlates with reduced preventable hiking incidents.

System Evolution: Technical priorities include enhancing logistics engine adaptability through user-customizable rules and machine learning, expanding the route and hazard database via data partnerships and crowdsourcing, and implementing community features such as collaborative trip reports to create a data-enriching feedback loop. Collectively, these steps will establish HikeSmart's real-world validity and scale its safety impact beyond the laboratory.

AUTHORS INFORMATION

Corresponding Author

Tikno – Department of Information Systems; Semen Indonesia International University. Email: tikno@uisi.ac.id

Authors

Anggit Mulianing Pambudi – Department of Information Systems; Semen Indonesia International University.

Citra Maulidya Haritsah – Department of Information Systems; Semen Indonesia International University.
Dinar Putra Mubarak – Department of Information Systems; Semen Indonesia International University.
Adinda Dwi Nur Rahmawati – Department of Information Systems; Semen Indonesia International University.

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COMPETING INTERESTS

The author declares that there are no competing interests related to this study. The author solely contributed to the conceptualization, data analysis, and manuscript preparation without any external influence that could bias the outcomes or interpretations presented in this article.

ETHICS STATEMENT

The author affirms that this research was conducted in accordance with established ethical standards. Any potential sources of bias, including financial, professional, or personal relationships, have been carefully considered and disclosed where applicable. The author has no financial interests, honoraria, patents, or affiliations that could be perceived as influencing the objectivity or integrity of this work. Transparency has been maintained to uphold scientific integrity and public trust.

DATA AVAILABILITY

The data supporting the findings of this study are available from the author upon reasonable request. Any datasets generated or analyzed during the study are stored in a secure repository and can be shared in compliance with data protection and privacy regulations.

CODE AVAILABILITY

The code used in this study is available upon reasonable request from the author. Where applicable, relevant scripts, models, or computational tools can be shared to facilitate reproducibility and further research.