INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue I January 2026

Integrating Real-Time Environmental Data and User Proficiency for Intelligent Trail Recommendation: A Thematic Review

Hidayah Rahmalan[1], Rasyidatul Aqilah Binti Ariff Iskandar [1], Ahmad Fadzli Nizam Abdul Rahman[1], Wan Mohd Ya'akob Wan Bejuri [2], Mohd Faiz Ibrahim Sawal[3]

[1]Fakulti Teknologi Maklumat & Komunikasi (FTMK), Universiti Teknikal Malaysia Melaka

[2]Fakulti Kecerdasan Buatan Dan Keselamatan Siber (FAIX), Universiti Teknikal Malaysia Melaka

[3]SME Bank Malaysia

DOI: https://doi.org/10.47772/IJRISS.2026.10100387

Received: 21 January 2026; Accepted: 26 January 2026; Published: 08 February 2026

ABSTRACT

Adventure tourism has experienced significant growth in recent years, with outdoor recreational activities such as hiking and mountaineering attracting millions of participants worldwide. However, the increasing popularity of trail-based activities has raised concerns about participant safety, environmental sustainability, and the need for personalized experiences that match individual capabilities. Traditional trail recommendation systems often rely on static information and fail to account for dynamic environmental conditions or real-time assessment of user proficiency levels. This paper proposes a thematic review for intelligent trail recommendation that integrates real-time environmental data streams with continuous user proficiency assessment to deliver safe, personalized, and context-aware trail suggestions. The proposed of this study leverages machine learning algorithms, Internet of Things (IoT) sensors, and semantic data models to process multi-dimensional data including weather conditions, terrain characteristics, trail difficulty metrics, and physiological indicators of user capability. We present a thematic review of existing approaches in trail recommendation systems, environmental data integration, user proficiency modeling, and safety-aware computing. This study reveals that while existing systems address individual components, there is a critical gap in holistic frameworks that seamlessly integrate environmental dynamics with user-specific capabilities. The proposed approach contributes to the advancement of intelligent tourism systems by providing a foundation for safer, more personalized outdoor recreational experiences that adapt to changing conditions and individual user profiles.

Keywords: Adventure Tourism, Trail Recommendation, Thematic review, User Proficiency, Safety-Aware Computing

INTRODUCTION

Adventure tourism represents one of the fastest-growing segments of the global tourism industry, with outdoor recreational activities such as hiking, mountaineering, and trail running attracting diverse participants ranging from casual enthusiasts to experienced adventurers. The proliferation of digital technologies, mobile computing, and location-based services has transformed how individuals plan, navigate, and experience outdoor activities. As tourism and recreational activities continue to expand globally, the demand for efficient, user-friendly booking platforms for specialized vehicles such as ATVs has grown substantially. The evolution of vehicle rental systems has been marked by a progressive shift from manual, paper-based processes to sophisticated digital platforms. Early research by Ogura et al. [1] introduced concepts of automated vehicle rental management, including excess-deficiency determination mechanisms that adjust rental fees to rebalance vehicle distribution across multiple locations. This foundational work established the principle that intelligent pricing mechanisms could address one of the most persistent challenges in vehicle rental operations: fleet imbalance. However, it was not related to ATV vehicles. In addition, this growth has been accompanied by increasing concerns about participant safety, environmental impact, and the need for personalized experiences that appropriately match individual capabilities with trail characteristics. The transition to digital platforms has been driven by the need to improve operational efficiency, reduce errors, and enhance customer satisfaction. Golo et al. [2] documented the challenges faced by traditional manual rental processes in tourism contexts, including unreliable service, booking difficulties, and inefficient fleet management. Their research on Siargao Island, Philippines, demonstrated that manual processes create significant barriers to both customer experience and business scalability, providing strong justification for automated online platforms. In current situation, the traditional approaches are still used to trail selection and recommendation have relied primarily on static information sources such as guidebooks, trail maps, and basic difficulty ratings. These conventional methods suffer from several critical limitations. First, they fail to account for dynamic environmental conditions that can significantly affect trail safety and accessibility, including weather changes, seasonal variations, and real-time hazards. Second, they typically employ simplistic, one-size-fits-all difficulty classifications that do not adequately consider the diverse range of user capabilities, experience levels, and physical fitness profiles. Third, they lack the ability to provide real-time guidance and adaptive recommendations as conditions change during outdoor activities.

Recent advances in several technological domains have created new opportunities for developing more sophisticated trail recommendation systems. The proliferation of Internet of Things (IoT) sensors enables continuous monitoring of environmental parameters such as temperature, precipitation, wind speed, and trail conditions. Wearable devices and smartphones equipped with physiological sensors can track user performance metrics including heart rate, perceived exertion, and movement patterns. Machine learning algorithms have demonstrated remarkable capabilities in processing complex, multi-dimensional data to generate personalized recommendations. Semantic web technologies and knowledge graphs provide frameworks for representing and reasoning about trail characteristics, user profiles, and contextual factors. Despite these technological advances, existing research and commercial systems have largely addressed these components in isolation. Trail recommendation systems have been developed that consider user preferences [3], difficulty assessment frameworks have been proposed using semantic data models [4], and environmental monitoring systems have been implemented for outdoor safety [5]. However, there remains a critical gap in comprehensive frameworks that seamlessly integrate real-time environmental data with dynamic user proficiency assessment to deliver intelligent, context-aware trail recommendations.

The central problem addressed in this research is the lack of holistic, intelligent trail recommendation systems that can simultaneously account for three critical dimensions:

(1) real-time environmental conditions and their dynamic changes,

(2) accurate assessment and continuous monitoring of user proficiency and capabilities, and

(3) safety-aware recommendation algorithms that balance user preferences with risk mitigation.

Current systems typically optimize for single objectives such as shortest distance, scenic value, or basic difficulty matching, without adequately considering the complex interplay between environmental factors, user capabilities, and safety requirements. This gap has significant practical implications. Inadequate trail recommendations can lead to dangerous situations where users encounter conditions beyond their capabilities, resulting in accidents, injuries, and rescue operations. Conversely, overly conservative recommendations may limit user experiences and fail to provide appropriate challenges for skilled participants. The absence of real-time environmental integration means that recommendations may become obsolete or dangerous as weather conditions change, trail hazards emerge, or seasonal factors alter trail characteristics. Adventure tourism, including motocross and ATV riding, is growing in popularity in Malaysia. While these activities provide economic and recreational benefits, many operators rely on manual booking methods such as walk-ins or messaging applications. These approaches cause scheduling errors, double-bookings, limited payment flexibility, and lack of customer guidance regarding trail suitability. Thus, the primary objectives of this study are to conduct a thematic review of existing approaches in trail recommendation systems, environmental data integration, user proficiency assessment, and safety-aware computing in the context of adventure tourism, and provide recommendations for future and development in this domain research.

Related Work

Trail recommendation systems have evolved significantly over the past decade, transitioning from simple distance-based routing to sophisticated personalized recommendation engines. Early systems focused primarily on finding optimal paths based on distance or time constraints, similar to conventional navigation applications. However, the unique characteristics of outdoor recreational activities including terrain complexity, elevation changes, scenic value, and safety considerations have necessitated more specialized approaches. Recent research has demonstrated the importance of personalization in trail recommendation. [3] conducted a comprehensive evaluation of leading outdoor recreation applications, identifying key features and limitations in current commercial systems. Their analysis revealed that while many applications provide basic trail information and user reviews, few incorporate sophisticated recommendation algorithms that account for individual user profiles and preferences. The study emphasized the need for systems that can adapt recommendations based on user experience levels, fitness capabilities, and specific interests. Semantic data models have emerged as a powerful approach for representing trail characteristics and difficulty assessment. [4] proposed a semantic framework for hiking trail difficulty assessment that goes beyond simple categorical ratings. Their approach utilizes ontologies to represent multiple dimensions of trail difficulty, including physical demands, technical requirements, and environmental factors. This semantic representation enables more nuanced matching between trail characteristics and user capabilities. Building on this foundation, [6] developed a platform for difficulty assessment and recommendation that integrates semantic models with user profiling and preference elicitation.

The SanTour system represents an early attempt at personalized trail recommendation based on health profiles [7]. This system considers user health conditions, fitness levels, and medical constraints when recommending hiking trails. The approach demonstrates the feasibility of incorporating physiological factors into recommendation algorithms, though it relies primarily on static user profiles rather than real-time physiological monitoring. Geographic information systems (GIS) and spatial analysis techniques have been widely employed in trail recommendation research. [8] developed a recommendation system for the Sierra de las Nieves Nature Reserve in Spain that combines network analysis with multi-criteria decision-making algorithms. Their approach considers factors such as trail length, elevation gain, scenic value, and accessibility to generate suitable and viable hiking routes. The system demonstrates how spatial analysis can be integrated with optimization algorithms to balance multiple objectives in trail recommendation.

Machine learning approaches have been increasingly applied to trail recommendation problems. [9] employed K-Nearest Neighbors (KNN) classification to match hikers with appropriate mountain locations based on their abilities. While this approach provides a data-driven method for ability-based recommendation, it relies on static classification and does not incorporate real-time environmental or physiological data. More sophisticated machine learning frameworks have been proposed for broader tourism recommendation contexts, with potential applications to trail recommendation [10].

Crowd-sourced data and user-generated content have become valuable resources for trail recommendation systems. [11] explored the use of crowd-sourced GPS traces from experienced mountaineers to generate personalized route recommendations. Their approach leverages the collective knowledge embedded in actual user trajectories to identify popular routes and variations that match individual preferences. This demonstrates the potential of leveraging community data to enhance recommendation quality, though it raises questions about data quality, representativeness, and the incorporation of less-traveled but potentially suitable routes.

Context-aware recommendation has been recognized as essential for outdoor recreation systems. [12] proposed a tourism and heritage route recommendation system that incorporates visitor profile adaptation and context awareness. Their framework considers temporal factors, weather conditions, and user preferences to generate adaptive recommendations. Similarly, [13] developed a system for analyzing and recommending outdoor activities in smart cities based on real-time contextual data, achieving high accuracy in activity recommendation through deep learning approaches.

The integration of environmental data into outdoor recreation systems has gained increasing attention as sensor technologies and IoT infrastructure have become more accessible and affordable. Environmental factors such as weather conditions, terrain characteristics, seasonal variations, and real-time hazards significantly impact trail safety and accessibility, yet many existing systems fail to adequately incorporate these dynamic factors.

Real-time environmental monitoring systems have been developed for various outdoor safety applications. [5] proposed a comprehensive framework for future outdoor safety monitoring that integrates human activity recognition with the Internet of Physical-Virtual Things. Their approach combines IoT sensors, wearable devices, and cloud computing to enable continuous monitoring of both environmental conditions and user activities. The system demonstrates the technical feasibility of real-time environmental data acquisition and processing, though it focuses primarily on safety monitoring rather than recommendation generation.

Weather data integration represents a critical component of environmental awareness in trail recommendation. While weather forecasts are widely available through various APIs and services, the challenge lies in translating weather data into actionable insights for trail recommendation. Factors such as precipitation, temperature, wind speed, and visibility can dramatically affect trail conditions and safety, but the relationship between weather parameters and trail suitability is complex and context-dependent. Terrain characteristics, elevation, and exposure all mediate how weather conditions impact specific trails.

Terrain analysis and elevation data have been extensively utilized in trail-related research. [14] developed a smart walking navigation system that incorporates geographical elevation data to calculate perceived exertion levels. Their system uses elevation profiles to estimate the physical demands of different routes, enabling recommendations that match user fitness capabilities. This demonstrates how terrain data can be integrated with physiological models to enhance recommendation quality.

Hazard detection and risk assessment based on environmental data remain challenging research areas. Social media data has been explored as a source of real-time hazard information. [14] utilized geo-tagged tweets to identify dangerous locations and scenic spots, demonstrating how crowd-sourced social media data can supplement traditional environmental data sources. However, the reliability, coverage, and timeliness of social media-based hazard detection require careful consideration. Seasonal variations and temporal dynamics of trail conditions represent another important dimension of environmental data integration. Trail accessibility and characteristics can change dramatically across seasons due to factors such as snow cover, vegetation growth, water levels, and wildlife activity. Few existing systems adequately model these temporal dynamics, instead relying on static trail information that may become outdated or inaccurate.

Complex event processing has been proposed as a methodology for handling real-time environmental data streams. [15] developed a complex event processing capability for intelligent environmental monitoring that can detect patterns and anomalies in streaming sensor data. Such approaches could be adapted for trail recommendation systems to identify emerging hazards or changing conditions that should trigger recommendation updates. The integration of environmental data with recommendation algorithms remains an open research challenge. While many systems collect environmental data, the translation of this data into recommendation logic requires sophisticated models that can assess how environmental factors affect trail suitability for different user profiles. This requires not only technical infrastructure for data acquisition and processing but also domain knowledge about the relationships between environmental conditions, trail characteristics, and user capabilities.

Accurate assessment of user proficiency and capabilities is fundamental to generating safe and appropriate trail recommendations. User proficiency encompasses multiple dimensions including physical fitness, technical skills, experience level, and psychological factors such as confidence and risk tolerance. Traditional approaches have relied on self-reported proficiency levels or simple categorical classifications, but these methods suffer from subjectivity, inconsistency, and inability to capture the multi-dimensional nature of outdoor recreation capabilities. Physiological monitoring has emerged as a promising approach for objective assessment of user capabilities. [14] incorporated heart rate data and perceived exertion models into their walking navigation system, demonstrating how physiological indicators can inform route recommendations. The system calculates expected exertion levels based on user characteristics (age, gender, resting heart rate) and route characteristics (distance, elevation), enabling personalized recommendations that match user fitness capabilities. However, this approach relies on predictive models rather than continuous real-time monitoring during activities.

Wearable devices and smartphones equipped with sensors enable continuous monitoring of physiological parameters during outdoor activities. Heart rate, movement patterns, GPS trajectories, and other sensor data can provide real-time insights into user performance and fatigue levels. This data could potentially be used to dynamically adjust recommendations or provide warnings when users are approaching their capability limits. However, the integration of real-time physiological monitoring into recommendation systems remains largely unexplored in the trail recommendation literature.

Skill-based proficiency assessment has been addressed through classification approaches. **[9]** employed machine learning classification to categorize hikers based on their abilities, using features such as experience level, physical fitness, and previous climbing history. Their KNN-based approach achieved reasonable accuracy in matching hikers with appropriate mountain locations. However, the system relies on static classification and does not adapt to changes in user capabilities over time or account for the multi-dimensional nature of hiking proficiency.

Experience-based proficiency modeling considers users' historical activity patterns and performance. Crowd-sourced trajectory data can provide insights into user capabilities based on the types of trails they have successfully completed. **[11]** leveraged GPS traces from experienced mountaineers to identify route patterns and preferences, implicitly capturing proficiency information through revealed preferences. This approach has the advantage of being based on actual performance rather than self-reported capabilities, but it requires substantial historical data and may not generalize well to new or infrequent users.

Multi-dimensional proficiency models have been proposed to capture the complexity of outdoor recreation capabilities. These models recognize that proficiency is not a single scalar value but rather a combination of physical, technical, cognitive, and psychological factors. For example, a user might have high physical fitness but limited technical climbing skills, or extensive experience but reduced physical capabilities due to age or health conditions. **[7]** incorporated health profiles into their SanTour system, considering medical conditions and physical limitations alongside general fitness levels.

Adaptive proficiency assessment that evolves based on user performance represents an important direction for future systems. As users’ complete trails and accumulate performance data, systems could refine their proficiency models to provide increasingly accurate assessments. Machine learning approaches could identify patterns in user performance across different trail types and conditions, enabling more nuanced proficiency profiles. However, such adaptive systems must balance personalization with privacy concerns and avoid creating filter bubbles that limit user exploration and growth. The challenge of proficiency assessment is further complicated by the context-dependent nature of capabilities. A user's effective proficiency may vary based on environmental conditions, equipment, group composition, and psychological state. A hiker who performs well in favorable conditions may struggle in adverse weather or challenging terrain. Few existing systems accounts for these contextual variations in proficiency assessment. Machine learning has become increasingly central to modern recommendation systems, offering powerful techniques for learning complex patterns from data and generating personalized recommendations. In the context of trail recommendation, machine learning approaches can address challenges such as multi-objective optimization, handling high-dimensional feature spaces, and learning from user feedback.

Collaborative filtering approaches have been widely applied in general recommendation systems but have seen limited application in trail recommendation. These methods leverage patterns in user-item interactions to identify similar users or items and generate recommendations. The challenge in applying collaborative filtering to trail recommendation lies in the sparsity of user-trail interaction data and the importance of content-based features (trail characteristics, environmental conditions) that collaborative filtering alone cannot capture. Content-based recommendation approaches utilize features of items (trails) and users to generate recommendations. These methods are particularly relevant for trail recommendation where trail characteristics (length, elevation gain, terrain type, difficulty) and user attributes (fitness level, experience, preferences) play crucial roles. Machine learning classifiers such as KNN have been employed for ability-based trail matching [9], demonstrating the feasibility of content-based approaches. However, simple classification methods may not capture the complex, non-linear relationships between trail features, user attributes, and suitability.

Hybrid recommendation approaches that combine collaborative filtering, content-based methods, and other techniques have shown promise in tourism recommendation. [10] proposed a conceptual framework for hybrid recommender systems in tourism based on big data and artificial intelligence. Their framework integrates multiple data sources and recommendation techniques to provide comprehensive, personalized recommendations. While not specifically focused on trail recommendation, the principles and architectures they propose are applicable to outdoor recreation contexts.

Deep learning approaches have demonstrated remarkable capabilities in learning complex representations and patterns from high-dimensional data. [13] employed deep learning for outdoor activity recommendation in smart cities, achieving accuracy rates exceeding 99% in activity classification and recommendation. Their approach processes real-time contextual data including weather, time, location, and user preferences to generate recommendations. Similarly, [16] applied deep learning to personalized travel route recommendation, demonstrating the potential of neural network architectures for route optimization problems.

Neural networks and deep learning have also been applied to tourist attraction recommendation with integration of IoT data. [17] developed a system that combines deep learning with Internet of Things sensors to recommend tourist attractions in smart cities. Their approach demonstrates how deep learning can process diverse data streams including sensor data, user preferences, and contextual information to generate real-time recommendations. The architecture and techniques they employ could be adapted for trail recommendation contexts. Multi-criteria decision-making (MCDM) approaches provide frameworks for balancing multiple, potentially conflicting objectives in recommendation. [18] employed the VIKOR method for trail ranking, considering factors such as scenic value, accessibility, environmental impact, and infrastructure. MCDM approaches are particularly valuable when recommendations must balance user preferences with safety constraints, environmental considerations, and other objectives that cannot be reduced to a single optimization criterion.

Reinforcement learning represents an emerging approach for adaptive recommendation systems that can learn from user feedback and environmental dynamics. While not yet widely applied in trail recommendation, reinforcement learning could enable systems that continuously improve recommendations based on user outcomes, adapting to changing conditions and learning optimal recommendation policies. The challenge lies in defining appropriate reward functions that balance user satisfaction with safety and other objectives.

Metaheuristic optimization algorithms have been applied to itinerary and route recommendation problems. [19] employed metaheuristic algorithms to improve itinerary recommendations for tourists, optimizing routes based on multiple constraints and preferences. These optimization approaches could be adapted for trail recommendation, particularly for multi-day trips or complex route planning scenarios. The integration of machine learning with domain knowledge and safety constraints remains a critical challenge. Pure data-driven approaches may generate recommendations that optimize for user preferences or historical patterns but fail to account for safety requirements or environmental constraints. Hybrid approaches that combine machine learning with rule-based safety checks and domain expertise are likely necessary for responsible trail recommendation systems.

Safety represents a paramount concern in adventure tourism and outdoor recreation, where participants face inherent risks from environmental hazards, physical challenges, and potential emergencies. Intelligent trail recommendation systems must prioritize safety while balancing user preferences and experience quality. This section reviews approaches to safety-aware computing in outdoor recreation contexts. Risk assessment and hazard identification form the foundation of safety-aware systems. [20] developed a safe walking route recommender that calculates fall risk using digital human models on 3D maps. Their approach simulates human movement on different terrain types to estimate tripping and falling risks, particularly for elderly users. While focused on urban walking rather than trail hiking, the methodology demonstrates how biomechanical modeling can inform safety-aware route recommendation. The system achieved significant risk reduction compared to shortest-path routing, validating the importance of explicit safety optimization.

Crowd-sourced safety data has been explored as a source of real-time hazard information. [21] developed a privacy-enhanced approach for safe route planning that leverages crowd-sourced travel experiences to identify hazardous locations. Their system computes personalized safety scores based on aggregated user experiences while preserving privacy through distributed computation. The approach demonstrates how collective knowledge can enhance safety awareness, though it focuses on urban road safety rather than trail-specific hazards. Wildlife encounter risks represent a specific safety concern in outdoor recreation. [22] investigated risk and preparedness in hiker-wildlife conflicts, identifying factors that contribute to dangerous encounters and strategies for risk mitigation. Their research highlights the importance of incorporating wildlife activity patterns, seasonal variations, and user preparedness into trail recommendation and safety systems. However, integrating such dynamic wildlife risk data into real-time recommendation systems remains technically challenging.

Emergency response and rescue considerations should inform trail recommendation systems. Trails that are remote, difficult to access, or lack communication infrastructure pose greater risks in emergency situations. Recommendation systems could incorporate factors such as cell phone coverage, proximity to emergency services, and trail traffic levels when assessing safety. However, few existing systems explicitly model emergency response capabilities in their recommendation logic. Safety validation and constraint checking represent important components of responsible recommendation systems. Even when machine learning algorithms generate recommendations optimized for user preferences, these recommendations should be validated against safety constraints before presentation to users. This might include checks for weather conditions, trail closures, user capability thresholds, and other safety-critical factors. The challenge lies in defining comprehensive safety rules that cover diverse scenarios without being overly restrictive.

User preparedness and safety education also play crucial roles in outdoor recreation safety. Recommendation systems could incorporate educational components that inform users about potential hazards, required equipment, and safety protocols for recommended trails. [23] explored design considerations for hiking safety and enjoyment, emphasizing the importance of user interface design and information presentation in promoting safe behaviors. As for this study, we are suggesting rider preparedness and safety while driving the ATV should choose suitable route and level of difficulties depending on their experiences. The balance between safety and user autonomy represents a fundamental tension in recommendation system design. Overly restrictive systems that prioritize safety above all else may limit user experiences and fail to provide appropriate challenges for skilled participants. Conversely, systems that defer entirely to user preferences without safety guardrails may enable dangerous decisions. Finding the appropriate balance requires careful consideration of user proficiency, risk tolerance, and the severity of potential consequences.

Real-time safety monitoring during activities extends beyond pre-trip recommendation to continuous assessment during outdoor activities. [5] proposed integrating human activity recognition with IoT-based environmental monitoring to enable real-time safety assessment. Such systems could detect when users are deviating from planned routes, experiencing unusual fatigue, or encountering hazardous conditions, triggering alerts or assistance. However, the technical infrastructure and user acceptance challenges for such continuous monitoring systems are substantial.

METHODOLOGY

This literature review adopts a thematic research framework designed to systematically analyze the intersection of digital technology and adventure tourism. A thematic review is a literature review approach that synthesizes prior studies by organizing them around key conceptual themes to identify patterns, gaps, and research opportunities. The methodology is structured around four primary research pillars identified as essential for modernizing trail management:

1. the evolution of personalized recommendation engines,

2. the integration of real-time environmental data,

3. the assessment of user proficiency, and

4. the implementation of safety-aware computing.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue I January 2026

This approach allows for a comprehensive evaluation of how outdoor recreational planning has transitioned from static, manual methods to sophisticated, location-based digital services. The methodology categorizes existing literature based on its technological and methodological domains to evaluate their efficacy in adventure contexts. The review investigates a range of computational approaches, including Machine Learning (KNN) for ability-based matching, Semantic Data Models for nuanced difficulty assessment, and Geographical Information Systems (GIS) for spatial optimization. Furthermore, the analysis examines the shift from static guidebooks to context-aware systems that utilize IoT sensors and weather APIs, such as wttr.in, to account for dynamic variables like precipitation and terrain hazards.

A critical component of this methodology is the execution of a gap analysis framework to identify deficiencies in current commercial and academic systems. The review specifically evaluates literature against a "central problem": the tendency of existing systems to address trail recommendation, environmental monitoring, and user assessment in isolation. By analyzing the complex interplay between these dimensions, the methodology identifies the lack of holistic, integrated frameworks that can simultaneously balance user preferences with objective risk mitigation and real-time environmental changes.

Finally, the methodology concludes with a synthesis of domain-specific findings tailored to the Malaysian adventure tourism sector. This phase involves documenting the operational inefficiencies of current manual booking processes, such as scheduling errors and fleet imbalances, and comparing them against the benefits of centralized digital platforms. The analysis culminates in a set of recommendations for future research, focusing on how emerging technologies like reinforcement learning and automated rider preparedness simulations can enhance safety and oversight in localized niche tourism.

RESULTS & FINDINGS

Our thematic review of existing trail recommendation systems reveals significant progress in individual components but also highlights critical gaps in holistic integration. The result of the thematic reviews of the domain is shown in Table 1 below.

Table 1 Thematic Review

Theme	Key Findings	Critical Gaps
Trail Recommendation Systems	Systems have evolved from simple distance-based routing to sophisticated engines using Machine Learning (KNN), GIS, and Semantic Data Models to match trail difficulty with user profiles.	Most systems optimize for a single objective (e.g., shortest distance or scenic value) and rely on static review data rather than dynamic conditions.
Environmental Data Integration	The use of IoT sensors and weather APIs (like wttr.in) allows for continuous monitoring of temperature, precipitation, and terrain hazards.	Existing frameworks often fail to translate raw environmental data into actionable insights or account for seasonal variations that alter trail accessibility.
User Proficiency Assessment	Research is shifting from subjective self-reporting to objective physiological monitoring using wearables to track heart rate and perceived exertion.	Proficiency assessments are typically static; there is a lack of continuous, real-time monitoring of user fatigue and evolving skill levels during an actual activity.
Safety-Aware Computing	Advanced models use biomechanical simulation to calculate fall risks and leverage crowd-sourced data to identify hazardous locations.	Systems rarely incorporate emergency response factors (e.g., cell coverage, proximity to help) or provide a validated safety check against machine learning recommendations

Table 2 presents a comparative analysis of key systems and approaches identified in the literature, evaluated across five dimensions: environmental data integration, user proficiency assessment, machine learning sophistication, safety mechanisms, and real-time adaptation capabilities.

Table 2 List of Comparative Analysis

Author(s) & Year	Environmental Data Used	User Proficiency / Profile Data	Algorithm / ML Approach	Safety-Related Features	Real-Time Adaptation
[14]	Elevation data; social-media-derived hazard information	Heart rate; perceived exertion	Dijkstra's algorithm	Hazard avoidance mechanisms	Limited
[9]	Static trail data	User ability level	K-Nearest Neighbors (KNN)	Basic ability matching	No
[4,6]	Static trail characteristics	Health profiles	Semantic reasoning	Difficulty level matching	No
[8]	GIS-based spatial data	User preferences	Multi-criteria optimization	Accessibility assessment	No
[13]	Real-time contextual data	Activity preferences	Deep learning (reported accuracy: 99.5%)	Not specified	Yes
[5]	IoT-based environmental sensor data	Activity recognition data	Pattern recognition techniques	Comprehensive monitoring	Yes

The analysis reveals several important patterns. First, systems that incorporate real-time environmental data [5,13] demonstrate superior adaptability but have not been specifically applied to trail recommendation contexts. Second, sophisticated user proficiency assessment remains rare, with most systems relying on simple self-reported levels or basic classification. Third, machine learning approaches vary widely in sophistication, from simple KNN classifiers to deep neural networks, but few systems employ hybrid approaches that combine multiple techniques. Fourth, safety mechanisms are often rudimentary, focusing on basic hazard avoidance rather than comprehensive risk assessment. Finally, real-time adaptation capabilities are limited in most trail-specific systems, despite being technically feasible as demonstrated in related domains. The semantic data modeling approach pioneered by [4,6] represents an important contribution to trail difficulty representation, enabling more nuanced matching between trail characteristics and user capabilities. However, these systems have not been integrated with real-time environmental monitoring or sophisticated machine learning recommendation engines. The SanTour system's incorporation of health profiles [7] demonstrates the feasibility of personalized recommendation based on user constraints, but relies on static profiles rather than dynamic assessment. The high accuracy achieved by deep learning approaches in related domains [13,17] suggests significant potential for applying these techniques to trail recommendation. However, the black-box nature of deep learning models raises concerns about explain ability and trust, particularly in safety-critical applications. Hybrid approaches that combine deep learning with interpretable models and rule-based safety validation may offer the best balance between performance and transparency. The integration of crowd-sourced data, as explored by [14] meanwhile [11] provides valuable real-world information that complements sensor data and official sources. However, data quality, reliability, and coverage remain challenges that must be addressed through validation mechanisms and appropriate weighting in recommendation algorithms.

CONCLUSION

This study has presented a comprehensive framework for intelligent trail recommendation that integrates real-time environmental data with dynamic user proficiency assessment to deliver safe, personalized, and context-aware recommendations for adventure tourism. We present a thematic review of existing approaches in trail recommendation systems, environmental data integration, user proficiency modeling, and safety-aware computing. The study reveals that while existing systems address individual components, there are still a critical gap in holistic integration, real-time adaptation, and multi-dimensional proficiency modeling that the proposed framework addresses. The proposed approach contributes to the advancement of intelligent tourism systems by providing a foundation for safer, more personalized outdoor recreational experiences that adapt to changing conditions and individual user profiles.

ACKNOWLEDGEMENT

The authors wish to express their sincere gratitude to Fakulti Teknologi Maklumat dan Komunikasi (FTMK) and Centre For Research And Innovation Management (CRIM) Universiti Teknikal Malaysia Melaka (UTeM) for their invaluable support in financial and facilitating this research.

REFERENCES

1. Ogura, K., Watanabe, T., Yano, S., & Terada, N. (2004). U.S. Patent Application No. 10/467,167.
2. Golo, M. A. T., & Encarnacion, R. E. (2024). Revolutionizing the Rental Services in Siargao Island: Basis for Developing an Online Vehicle Rental Management System. International Journal of Advanced Research in Science. Tongxin Jishu, 438-439.
3. Hamza-Mayora, S., Labrador-Roca, V., & Fernández-Piqueras, R. (2025). Recommender systems for hiking and mountaineering: A conceptual framework and evaluation of leading outdoor apps. Journal of Outdoor Recreation and Tourism, 52, 100959.
4. Calbimonte, J. P., Martin, S., Calvaresi, D., Zappelaz, N., & Cotting, A. (2019, December). Semantic data models for hiking trail difficulty assessment. In Information and Communication Technologies in Tourism 2020: Proceedings of the International Conference in Surrey, United Kingdom, January 08–10, 2020 (pp. 295-306). Cham: Springer International Publishing.
5. Chen, Y., Li, J., Blasch, E., & Qu, Q. (2025). Future Outdoor Safety Monitoring: Integrating Human Activity Recognition with the Internet of Physical–Virtual Things. Applied Sciences, 15(7), 3434.
6. Calbimonte, J. P., Martin, S., Calvaresi, D., & Cotting, A. (2021, January). A platform for difficulty assessment and recommendation of hiking trails. In Information and Communication Technologies in Tourism 2021: Proceedings of the ENTER 2021 eTourism Conference, January 19–22, 2021 (pp. 109-122). Cham: Springer International Publishing.
7. Calbimonte, J. P., Zappellaz, N., Hébert, E., Simon, M., Délétroz, N., Hilfiker, R., & Cotting, A. (2018, June). SanTour: towards personalized recommendation of hiking trails to health profiles. In International Conference on Web Engineering (pp. 238-250). Cham: Springer International Publishing.
8. Vías, J., Rolland, J., Gómez, M. L., Ocaña, C., & Luque, A. (2018). Recommendation system to determine suitable and viable hiking routes: a prototype application in Sierra de las Nieves Nature Reserve (southern Spain). Journal of Geographical Systems, 20(3), 275-294.
9. Al Fathony, S. H., Rahajoe, A. D., & Zainal, R. F. (2022). KNN and Webgis Classification to Recommend Mountain Location According to Hiker Abilities. JEECS (Journal of Electrical Engineering and Computer Sciences), 7(1), 1239-1246.
10. Al Fararni, K., Nafis, F., Aghoutane, B., Yahyaouy, A., Riffi, J., & Sabri, A. (2021). Hybrid recommender system for tourism based on big data and AI: A conceptual framework. Big Data Mining and Analytics, 4(1), 47-55.
11. Daiber, F., Kosmalla, F., Wiehr, F., & Krüger, A. (2017, September). Follow the pioneers: towards personalized crowd-sourced route generation for mountaineers. In Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017

ACM International Symposium on Wearable Computers (pp. 1051-1055).
12. Hoque, T. T., Ferreira, L., Faria, L., Martins, C., Mesquita, R., Conceição, L., ... & Ramos, C. (2018, December). Tourism and Heritage Routes Including Visitants Profile Adaptation and Context Awareness. In 2018 International Conference on Computational Science and Computational Intelligence (CSCI) (pp. 947-953). IEEE.
13. Sekhar, S. M., Ahmed, D. M., & Siddesh, G. M. (2024). Analysis and recommendation of outdoor activities for smart city users based on real-time contextual data. Computing Open, 2, 2450004.
14. Siriaraya, P., Wang, Y., Zhang, Y., Wakamiya, S., Jeszenszky, P., Kawai, Y., & Jatowt, A. (2020). Beyond the shortest route: A survey on quality-aware route navigation for pedestrians. IEEE Access, 8, 135569-135590.
15. Sun, A. Y., Zhong, Z., Jeong, H., & Yang, Q. (2019). Building complex event processing capability for intelligent environmental monitoring. Environmental modelling & software, 116, 1-6.
16. Huang, X. (2022). Personalized travel route recommendation model of intelligent service robot using deep learning in big data environment. Journal of Robotics, 2022(1), 7778592.
17. Cepeda-Pacheco, J. C., & Domingo, M. C. (2022). Deep learning and Internet of Things for tourist attraction recommendations in smart cities. Neural Computing and Applications, 34(10), 7691-7709.
18. Kolkos, G., Kantartzis, A., Stergiadou, A., & Arabatzis, G. (2024). Development of Semi-Mountainous and Mountainous Areas: Design of Trail Paths, Optimal Spatial Distribution of Trail Facilities, and Trail Ranking via MCDM-VIKOR Method. Sustainability, 16(22), 9966.
19. Tenemaza, M., Luján-Mora, S., De Antonio, A., & Ramirez, J. (2020). Improving itinerary recommendations for tourists through metaheuristic algorithms: an optimization proposal. Ieee Access, 8, 79003-79023.
20. Minakata, M., Maruyama, T., Tada, M., Ramasamy, P., Das, S., & Kurita, Y. (2022). Safe Walking Route Recommender Based on Fall Risk Calculation Using a Digital Human Model on a 3D Map. IEEE Access, 10, 8424-8433.
21. Islam, F. T., Hashem, T., & Shahriyar, R. (2023). A crowd-enabled approach for privacy-enhanced and personalized safe route planning for fixed or flexible destinations. IEEE Transactions on Knowledge and Data Engineering, 35(11), 10922-10936.
22. Cao, Y., Hassan, T., Fan, J., Saaty, M., Wang, W. L., Stelter, T. L., & McCrickard, S. (2025, April). Listening to the Wild: Risk and Preparedness in Hiker-Wildlife Conflicts during Outdoor Recreation. In Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems (pp. 1-8).
23. Wu, T. (2021). Design for Hiking Safety and Fun. Rochester Institute of Technology.