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An Adaptive Hybrid Recommender System for Smart Tourism Using User Preferences, Context and Artificial Intelligence

Kasturi B. Verulkar[#1], Raksha D. Bhude[#2], Payal S. Gajbhiye[#3] , Prof. B.S. Sheikh[#4]

[#1,2,3,4] Department of Computer Engineering,

Smt. Radhikatai Pandav College of Engineering, Nagpur, Maharashtra, India.

ABSTRACT:-

The rapid growth of digital tourism platforms, mobile applications, online reviews, and location-based services has created a large volume of heterogeneous tourism information. Although this information provides tourists with numerous choices, it can also make destination selection and travel planning difficult. This paper proposes an Adaptive Hybrid Recommender System for Smart Tourism Using User Preferences, Context and Artificial Intelligence to provide more personalized and relevant tourism recommendations. The proposed framework considers explicit preferences, previous interactions, behavioral patterns, tourism resource characteristics, and contextual information to develop a comprehensive understanding of individual tourists.

The proposed system combines hybrid recommendation techniques with artificial intelligence and context-aware processing to improve the relevance of tourism suggestions. Factors such as location, available travel time, budget, weather conditions, activity preferences, and previously visited destinations can be incorporated into the recommendation process. Unlike static recommendation approaches, the proposed framework is designed to adapt its recommendations when user interests or travel conditions change. It also supports personalized itinerary generation by selecting and organizing suitable tourism resources according to the user's preferences and practical travel constraints.

The proposed framework provides a unified approach for intelligent tourism applications by integrating adaptive user profiling, contextual information, hybrid recommendation, and dynamic travel planning. It aims to reduce information overload, improve personalization, and support tourists in making more informed travel decisions. The framework can be implemented using scalable Big Data technologies and machine learning methods and can subsequently be evaluated using real-world tourism datasets and appropriate recommendation performance measures. The study provides a foundation for developing adaptive and intelligent tourism recommendation systems capable of responding to changing user preferences and travel environments.

Keywords: Smart Tourism, Hybrid Recommender System, Artificial Intelligence, Big Data, Personalized Tourism, Context-Aware Recommendation, Adaptive Recommendation, User Profiling, Machine Learning, Dynamic Itinerary Planning.

I. INTRODUCTION

The rapid growth of digital technologies has significantly changed the way people search for, select, and experience tourism services. Travelers can now access a large variety of information through websites, mobile applications, online reviews, social media platforms, digital maps, and location-based services. Information about destinations, hotels, restaurants, attractions, transportation, activities, prices, and events is continuously generated and updated. Although this availability of information provides travelers with greater choice, it also creates a significant decision-making challenge. A traveler may need to evaluate hundreds of possible destinations and services while considering personal interests, available time, budget, geographical location, and changing travel conditions. Consequently, intelligent systems that can reduce information overload and provide personalized recommendations have become increasingly important in modern tourism.

Recommender systems provide an effective approach for assisting users in making decisions from large collections of available alternatives. Traditional recommendation techniques generally rely on information such as item characteristics, user preferences, previous interactions, or similarities between users. Content-based approaches recommend items that are similar to those previously preferred by a user, while collaborative approaches identify recommendations by analyzing relationships between users and their historical choices. However, tourism recommendation is more complex than recommending an isolated product or service. A suitable tourism recommendation may depend simultaneously on several factors, including destination characteristics, user interests, travel duration, budget, location, season, weather, time of day, and previously visited places. A recommendation that is appropriate under one set of circumstances may become unsuitable when the user's preferences or travel conditions change. Therefore, tourism recommendation requires a more flexible approach capable of combining multiple sources of information and adapting recommendations according to the current context.

Artificial Intelligence (AI) provides opportunities to develop such adaptive recommendation mechanisms. Machine learning techniques can identify patterns in user behavior, learn from historical interactions, estimate user preferences, and improve recommendations over time. At the same time, contextual information can provide additional knowledge about the circumstances in which a recommendation is requested. For example, the same traveler may prefer a historical attraction during the morning, an indoor activity during unfavorable weather, or a low-cost activity when the available budget is limited. Incorporating these factors into recommendation generation can make the resulting suggestions more relevant than recommendations based only on static user profiles.

Another important challenge is that tourism decisions are interconnected. Selecting a destination or attraction is often only the first step; travelers must also determine which places should be visited, in what order, and within what time and resource constraints. A collection of individually relevant recommendations does not necessarily constitute a practical

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travel plan. For example, several highly rated attractions may be located far apart, have incompatible opening times, or exceed the traveler's available budget or time. This creates a need for an intelligent mechanism that can transform personalized recommendations into a feasible itinerary while considering relationships among recommended tourism resources.

The proposed research introduces an Adaptive Hybrid Recommender System for Smart Tourism Using User Preferences, Context and Artificial Intelligence. The central idea is to integrate multiple recommendation perspectives rather than depending on a single recommendation technique. The proposed approach considers explicit user preferences together with historical interactions, behavioral patterns, tourism-resource characteristics, and contextual information. These inputs can be processed through AI-based methods to estimate the relevance of available tourism options and continuously adapt the recommendation process according to changes in user interests and travel conditions.

The proposed system further extends recommendation generation toward dynamic itinerary planning. Instead of presenting a simple list of recommended destinations or services, the system is intended to identify a suitable combination of tourism activities and organize them according to user requirements and practical constraints. Factors such as available travel time, budget, geographical relationships, preferred activities, and contextual conditions can be considered during itinerary generation. This creates a connection between personalized recommendation and intelligent travel planning, enabling the system to provide recommendations that are not only individually relevant but also collectively useful.

The research is motivated by the need for tourism recommendation systems that are more adaptive, context-aware, and capable of handling heterogeneous information. Large-scale tourism environments generate continuously changing data, making scalability an important consideration for future implementation. A system based on scalable data-processing technologies and machine-learning techniques can potentially process diverse tourism information while maintaining the flexibility required for personalized recommendations. The proposed framework therefore provides a foundation for integrating user modeling, contextual analysis, hybrid recommendation, AI-based adaptation, and dynamic itinerary planning within a unified smart tourism environment.

The main contribution of this research is the design of an adaptive conceptual framework that combines these components into a coordinated recommendation process. The framework emphasizes continuous user profiling, multi-source recommendation, contextual adaptation, and itinerary generation rather than treating each function as an independent component. It is intended to reduce the effort required by travelers to evaluate large amounts of tourism information and to support more personalized and context-sensitive travel decisions.

The remainder of this paper is organized as follows. Section 2 discusses the relevant literature and existing approaches to tourism recommender systems, hybrid recommendation, contextual recommendation, and AI-based personalization. Section 3 presents the proposed adaptive hybrid recommender framework and its major components. Section 4 describes the proposed recommendation methodology and system workflow. Section 5 presents the proposed model for dynamic itinerary generation and evaluation. Section 6 discusses the expected advantages, limitations, and implementation considerations of the framework. Finally, Section 7 concludes the research and identifies possible directions for future development and empirical validation.

II. RELATED WORK

Tourism recommender systems have received increasing attention as digital tourism platforms generate large volumes of information about destinations, attractions, accommodation, transportation, activities, and other travel-related services. The diversity of available information creates opportunities for personalized tourism services but also makes it difficult for travelers to identify alternatives that match their individual requirements. Existing research has therefore investigated different recommendation techniques for identifying relevant tourism resources and supporting travel decision-making. The major approaches relevant to the proposed research include content-based recommendation, collaborative recommendation, demographic recommendation, hybrid recommendation, context-aware recommendation, and itinerary-oriented recommendation

1. Content-Based Recommendation

Content-based recommendation is one of the fundamental approaches used to generate personalized suggestions. In this approach, recommendations are derived primarily from the characteristics of tourism resources and the user's previously expressed interests or interactions. Tourism items can be represented using attributes such as destination category, activity type, geographical characteristics, facilities, or descriptive information. The system compares these characteristics with the user's preference profile and identifies resources having a high degree of relevance.

The main advantage of content-based recommendation is its ability to provide individualized results without requiring information from a large community of users. It can therefore be useful when sufficient information about the characteristics of tourism resources and a user's interests is available. However, relying mainly on item characteristics can limit the diversity of recommendations. It may also become difficult to recommend unfamiliar resources when the system has limited information about the user's interests. These limitations motivate the integration of additional recommendation techniques.

2. Collaborative Recommendation

Collaborative recommendation uses interactions and preferences collected from multiple users. Instead of relying exclusively on the characteristics of an individual tourism resource, the system identifies relationships among users and their choices. Travelers with similar behavioral patterns can provide useful information for generating recommendations to one another. In a tourism environment, collaborative techniques can utilize information such as ratings, reviews, selections, visits, or other forms of user interaction. This approach can improve recommendation diversity because the system can introduce resources that a particular traveler has not previously considered. Nevertheless, collaborative recommendation can experience difficulties when new users have insufficient historical interactions or when newly introduced tourism resources have limited feedback. This is commonly associated with the cold-start

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challenge and demonstrates the value of combining collaborative information with other sources of evidence.

3. Demographic-Based Recommendation

Demographic information can also be incorporated into recommendation processes. Characteristics associated with user groups can be used to identify general patterns in tourism preferences. For example, users belonging to similar demographic categories may demonstrate comparable interests in certain types of destinations or activities.

Demographic recommendation can provide useful initial recommendations when limited personal interaction history is available. However, demographic characteristics alone cannot completely represent an individual's preferences. Two users belonging to the same demographic group may have substantially different travel interests, budgets, activity preferences, and behavioral patterns. Consequently, demographic information is more suitable as one component of a broader user model rather than as the sole basis for personalized tourism recommendation.

4. Hybrid Recommender Systems

The limitations associated with individual recommendation techniques have encouraged the development of hybrid recommender systems. A hybrid system combines two or more recommendation strategies so that information from different sources can contribute to the final recommendation. In tourism applications, content characteristics, collaborative information, demographic attributes, and user interactions can be combined to improve recommendation relevance. Hybridization is particularly relevant to tourism because tourism preferences are multidimensional. A traveler may select a destination based on personal interests while simultaneously considering previous experiences, similarity to other travelers, price, distance, and available activities. Combining different recommendation perspectives can therefore provide a richer representation of user preferences than a single recommendation method.

The reference study also identifies hybridization as an important component of a tourism recommendation architecture, where content-based, collaborative/social, and demographic recommendation mechanisms can contribute to the filtering process. However, the proposed research extends this direction by emphasizing adaptive behavior and contextual changes rather than treating hybrid recommendation only as a combination of filtering techniques.

5. Context-Aware Recommendation

Tourism decisions are strongly influenced by circumstances surrounding the user. Context-aware recommendation attempts to incorporate such information into the recommendation process. Relevant contextual factors may include geographical location, travel time, season, weather conditions, budget limitations, availability, and the activities currently preferred by the traveler.

The importance of contextual information arises from the fact that user preferences are not necessarily constant. A traveler may prefer outdoor activities under favorable weather conditions but select indoor alternatives when weather conditions change. Similarly, the relevance of a tourism attraction can depend on the traveler's current location and the amount of time available.

Context-aware recommendation can therefore make tourism suggestions more responsive to real-world conditions. **Nevertheless, contextual** information introduces additional complexity because multiple contextual variables may need to be processed simultaneously. An effective system must determine which contextual factors are relevant to a particular recommendation request and how strongly each factor should influence the final result

6. User Profiling and Preference Modeling

Accurate user modeling is an important foundation for personalized recommendation. A tourism recommender can construct a user profile from explicitly provided information as well as implicitly observed interactions. Explicit information ma include preferred activities, destination interests, budget ranges, or travel constraints. Implicit information can be derived from actions such as searches, clicks, ratings, viewed destinations, saved resources, and previous selections.

The reference framework considers several possible sources for user profiling, including registration information, social-login information, user behavior during system interaction, and contextual information. These different sources demonstrate that a tourism profile can evolve as more information about the traveler becomes available.

For the proposed system, user profiling is considered a continuous process rather than a one-time activity. The user's current preferences can be combined with historical behavior and contextual information to generate an adaptive representation. Such a representation can help the recommendation mechanism respond when a traveler's interests change over time.

7. Tourism Itinerary and Trip Planning

Recommendation of individual tourism resources is only one part of the travel-planning problem. Travelers often need to combine several attractions and activities into a practical sequence. Consequently, research on tourism recommender systems has also considered itinerary or trip planning, where multiple recommended resources are organized according to travel requirements and constraints. An itinerary must consider relationships among tourism resources. Geographic distance, visiting time, opening periods, available travel duration, budget, and user preferences may influence whether a collection of recommended places can be included in the same trip. The reference framework similarly identifies trip planning as a stage in which relevant recommended items are selected and organized while considering contextual conditions and planning constraints.

This indicates an important distinction between recommendation relevance and itinerary feasibility. A tourism resource may be individually relevant to a traveler but unsuitable for a particular itinerary because of time, distance, cost, or scheduling restrictions. Therefore, an effective smart tourism system should evaluate both the attractiveness of individual resources and their compatibility within a complete travel plan.

8. Artificial Intelligence and Large-Scale Tourism Data

The increasing volume and diversity of tourism information provide an important role for Artificial Intelligence

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and scalable data-processing techniques. Tourism platforms can contain heterogeneous information originating from users, tourism providers, online interactions, location services, and other digital sources. Processing this information can support more detailed user profiles and more adaptive recommendation models.

The reference research discusses the integration of tourism data aggregation, recommendation, visualization, and validation within a Big Data-oriented architecture, with technologies such as NoSQL-based storage, distributed processing, machine learning, and other AI-related techniques considered as part of the broader implementation direction.

For the proposed research, AI is considered primarily as an adaptive mechanism capable of learning patterns from user interactions and improving recommendation decisions. Large-scale data technologies can provide the underlying infrastructure required when tourism data becomes sufficiently large and heterogeneous. The combination of these technologies creates the possibility of developing recommendation systems that continuously learn from new information rather than depending entirely on static rules.

9. Research Gap

The reviewed approaches demonstrate that tourism recommendation has evolved from relatively independent filtering methods toward systems that combine multiple recommendation strategies and additional contextual information. Content-based methods provide personalization based on resource characteristics, collaborative approaches utilize collective user behavior, demographic methods provide group-level information, and hybrid systems combine multiple recommendation perspectives. Context-aware approaches further improve the relevance of recommendations by considering the circumstances under which a recommendation is requested.

Despite these developments, an important challenge remains in connecting adaptive personalization, contextual recommendation, and practical itinerary generation within a unified process. A recommendation system may identify highly relevant individual resources without determining whether those resources can form a coherent travel plan. Similarly, a static user profile may fail to reflect changes in interests or travel circumstances. These issues indicate the need for a system that can continuously update user preferences, combine multiple recommendation signals, incorporate contextual information, and transform the resulting recommendations into a feasible itinerary.

The proposed research addresses this gap through an Adaptive Hybrid Recommender System for Smart Tourism Using User Preferences, Context and Artificial Intelligence. Instead of considering user profiling, recommendation, contextual analysis, and itinerary generation as isolated functions, the proposed framework connects them into an adaptive pipeline. The intended contribution is a conceptual model in which user preferences and behavioral information are continuously combined with tourism-resource characteristics and current context, while AI-based processing supports adaptive recommendation and dynamic itinerary planning.

This research direction is related to the hybrid tourism recommendation architecture presented in the reference study, but it introduces a distinct emphasis on adaptation to changing user preferences and contextual conditions and on the relationship between recommendation quality and itinerary feasibility. The proposed framework will subsequently define the architecture, recommendation methodology, adaptive scoring mechanism, and itinerary-generation process required to investigate this approach.

III. PROPOSED SYSTEM AND METHODOLOGY

1. Overview of the Proposed System

This research proposes an Adaptive Hybrid Recommender System for Smart Tourism Using User Preferences, Context and Artificial Intelligence. The proposed system is designed to generate personalized tourism recommendations by combining user preferences, historical interactions, tourism-resource characteristics, and current contextual conditions.

Unlike a conventional recommendation system that generates recommendations primarily from a fixed user profile, the proposed approach treats the user's preference model as dynamic. The system continuously updates the estimated preference of a traveler according to new interactions and changes in travel context. The resulting recommendations can therefore change when the user's interests, location, available time, budget, or other relevant conditions change.

The proposed methodology consists of six major stages:

- Tourism data acquisition and preparation
- Dynamic user preference modeling
- Context identification and analysis
- Hybrid recommendation generation
- Adaptive recommendation scoring
- Dynamic itinerary generation

These stages operate as an integrated process. The output of one stage becomes input to the next stage, while user interactions with the generated recommendations can subsequently be used to update the user model.

2. Overall System Architecture

The proposed architecture is organized into interconnected functional layers rather than treating recommendation and trip planning as independent processes.

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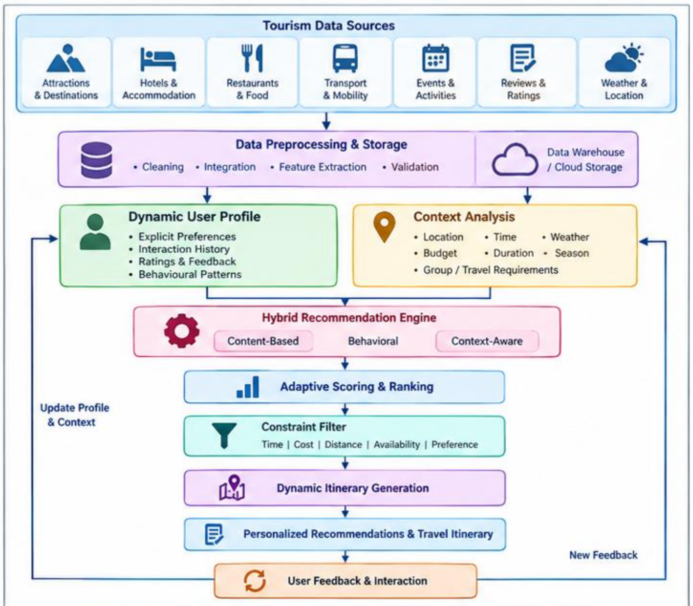

Figure 1. Overall architecture of the proposed adaptive hybrid recommender system for smart tourism.

Layer 1: Tourism Data Layer

The tourism data layer contains information required for recommendation generation. Possible data categories include:

- Destination information
- Tourist attractions
- Hotels and accommodation
- Restaurants and food services
- Transportation information
- Recreational activities
- Historical and cultural sites
- Tourism-event information
- Pricing information
- Geographic information
- User ratings and reviews
- Availability information

The proposed system is designed to accommodate heterogeneous tourism information. Data may originate from tourism databases, application interfaces, user-generated content, digital platforms, or other authorized tourism information sources.

Before recommendation generation, the collected information is processed to remove inconsistent, incomplete, or duplicate records where appropriate. Relevant attributes are transformed into a representation that can be used by the recommendation engine.

3. Dynamic User Preference Model

A central component of the proposed methodology is the dynamic user preference model. Instead of representing a traveler using only static demographic information, the model combines multiple forms of preference evidence.

The user model can contain:

- Explicit preferences
- Previous tourism selections
- Ratings and feedback
- Search and browsing behavior
- Frequently selected activity categories
- Preferred price range
- Preferred distance
- Travel duration
- Previously visited destinations
- Current travel requirements

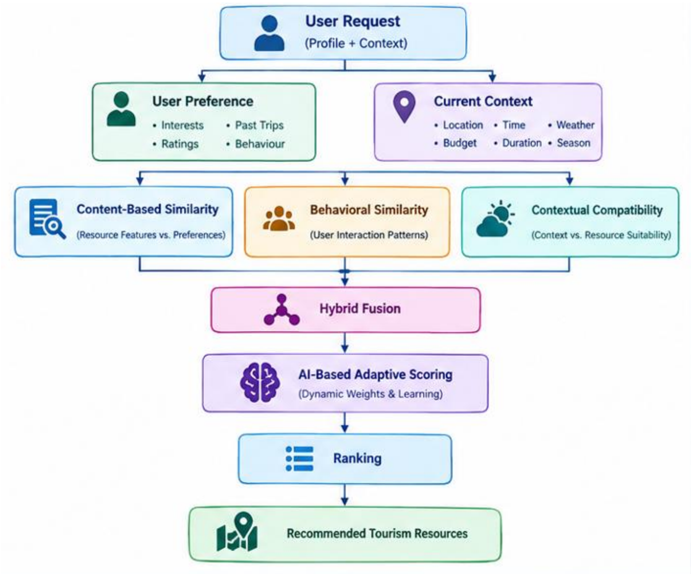

Figure 2. Hybrid recommendation and adaptive ranking process.

Explicit preferences are obtained directly from the traveler. For example, a user may specify interests such as historical places, adventure activities, nature tourism, food experiences, or cultural attractions.

Implicit preferences are derived from interactions with the system. Repeatedly viewing, selecting, saving, rating, or rejecting a particular category can provide additional evidence regarding the user's interests.

The system combines these signals to create an adaptive preference representation.

A simplified preference score for a tourism category can be represented as:

$$P(u,c)=\alpha E(u,c)+\beta H(u,c)+\gamma B(u,c)$$

where:

- ($P(u,c)$) = estimated preference of user (u) for category (c)
- ($E(u,c)$) = explicit preference score
- ($H(u,c)$) = historical interaction score
- ($B(u,c)$) = behavioral preference score
- (α,β,γ) = weighting parameters

The weights can be adjusted during system development and evaluation. This formulation is intended as a proposed model and does not represent experimentally established values.

4. Context Identification

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User preferences alone may not be sufficient to generate appropriate tourism recommendations. The proposed system therefore introduces a separate contextual analysis stage.

Relevant context may include:

- Current or selected location
- Travel date
- Available travel duration
- Budget
- Weather condition
- Time of day
- Season
- Group or travel requirements
- Current activity preference
- Distance from the traveler
- Availability of tourism resources

Context is represented as a set of variables associated with a particular recommendation request:

[
C={L,T,D,B,W,S,A,R}
]

where:

(L) = location
(T) = time
(D) = available duration
(B) = budget
(W) = weather condition
(S) = season
(A) = activity requirement
(R) = resource availability

The contextual model enables the system to distinguish between long-term user preferences and temporary travel requirements.

for example, a traveler may generally prefer outdoor tourism. However, if the current weather is unfavorable, the system can reduce the priority of outdoor activities and consider suitable indoor alternatives. In this manner, contextual information can modify the recommendation without permanently changing the user's long-term preference profile.

IV. ARTIFICIAL INTELLIGENCE COMPONENT

Artificial Intelligence is incorporated into the proposed system to support preference learning, recommendation adaptation, and future prediction.

The AI component can perform the following functions:

- Identify patterns in user interactions
- Estimate changing user interests
- Classify tourism resources
- Predict resource relevance
- Detect relationships between user characteristics and tourism choices
- Update recommendation priorities
- Support personalized ranking
- Improve itinerary selection

Machine-learning models can be trained using historical tourism interaction data when sufficient data becomes available. The proposed methodology does not prescribe a single machine-learning algorithm because the appropriate model should be selected based on the characteristics and volume of the actual dataset.

This allows the framework to support different machine-learning techniques during implementation and experimentation.

V. CONTINUOUS ADAPTATION AND FEEDBACK

An important feature of the proposed system is the feedback loop.
After receiving recommendations, users may:

- Select a recommendation
- Reject a recommendation
- View additional information
- Rate a tourism resource
- Save a resource
- Remove a resource
- Modify budget or time constraints
- Change activity preferences

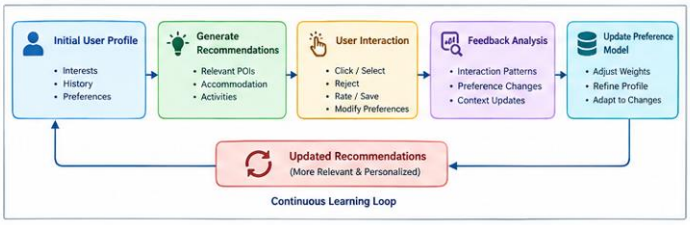

Figure 3. Continuous adaptation mechanism based on user feedback.

These actions provide new information to the user model.

The system can therefore follow the cycle:

Recommendation → User Interaction → Preference Update → Context Update → New Recommendation

This feedback mechanism allows the recommendation process to become adaptive rather than remaining fixed throughout the user's travel-planning session.

For example, if a traveler repeatedly rejects adventure activities and selects cultural attractions, the system can increase the estimated preference for cultural tourism during subsequent recommendation cycles.

VI. DYNAMIC ITINERARY GENERATION

The final stage transforms the selected tourism resources into a practical itinerary.

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The itinerary-generation process considers:

- User preferences
- Recommendation scores
- Geographic distance
- Travel time
- Opening or availability constraints
- Available trip duration
- Budget
- Activity compatibility
- Contextual conditions

Let an itinerary be represented by:

$$R=\{i_1,i_2,\ldots,i_k\}$$

where each (i_j) represents a selected tourism resource.

The objective is not simply to maximize the recommendation score of individual resources. Instead, the system attempts to identify a combination that provides high overall relevance while satisfying travel constraints.

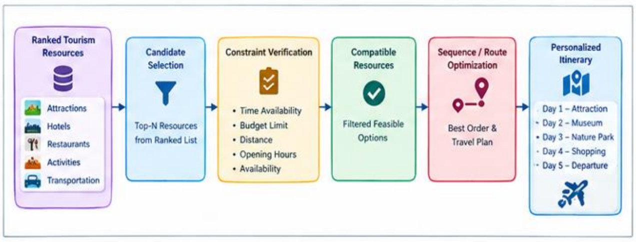

Figure 4. Proposed dynamic itinerary-generation process.

A conceptual itinerary objective can be represented as:

$$F(R)=\lambda_1 Rel(R)+\lambda_2 Ctx(R)+\lambda_3 Div(R)-\lambda_4 Cost(R)-\lambda_5 TimeViolation(R)$$

where:

$(Rel(R))$ = overall recommendation relevance
$(Ctx(R))$ = contextual suitability
$(Div(R))$ = recommendation diversity
$(Cost(R))$ = total estimated travel/resource cost
$(TimeViolation(R))$ = violation of available time or scheduling constraints
$(\lambda_1,\lambda_2,\lambda_3,\lambda_4,\lambda_5)$ = weighting parameters

The objective is to identify an itinerary that provides a suitable balance between personalization, contextual relevance, diversity, cost, and feasibility.

VII. CONCLUSION

This research proposed an **Adaptive Hybrid Recommender System for Smart Tourism Using User Preferences, Context and Artificial Intelligence**. The proposed framework integrates dynamic user profiling, content-based recommendation, behavioral information, contextual analysis, adaptive scoring, and dynamic itinerary generation into a unified tourism recommendation process.

The main objective of the proposed system is to provide more personalized and context-sensitive tourism recommendations while reducing the difficulty of selecting suitable tourism resources from large and heterogeneous information sources. The proposed feedback mechanism also allows user interactions to influence subsequent recommendations, making the system adaptive to changing preferences and travel conditions.

The framework provides a conceptual foundation for future implementation using real tourism datasets, machine-learning techniques, and scalable data-processing technologies. Future work will focus on developing a working prototype, selecting and evaluating appropriate AI algorithms, testing the proposed scoring model using real user and tourism data, and measuring recommendation accuracy, diversity, personalization, and itinerary feasibility. Experimental validation will be necessary to determine the actual effectiveness of the proposed approach.

REFERENCE

[1] L. Sebastia, I. García, E. Onaindia, and C. Guzman Alvarez, “e-Tourism: A tourist recommendation and planning application,” *International Journal on Artificial Intelligence Tools*, vol. 18, no. 5, pp. 717–738, 2009.

[2] F. Ricci, L. Rokach, and B. Shapira, “Introduction to recommender systems handbook,” in *Recommender Systems Handbook*, F. Ricci, L. Rokach, B. Shapira, and P. Kantor, Eds. Boston, MA, USA: Springer, 2011, pp. 1–35.

[3] G. Adomavicius and A. Tuzhilin, “Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions,” *IEEE Transactions on Knowledge and Data Engineering*, vol. 17, no. 6, pp. 734–749, 2005.

[4] M. de Gemmis, P. Lops, C. Musto, F. Narducci, and G. Semeraro, “Semantics-aware content-based recommender systems,” in *Recommender Systems Handbook*, F. Ricci, L. Rokach, and B. Shapira, Eds. Boston, MA, USA: Springer, 2015, pp. 119–159.

[5] S. Loh, F. Lorenzi, R. Saldana, and D. Lichtnow, “A tourism recommender system based on collaboration and text analysis,” *Information Technology & Tourism*, vol. 6, no. 3, pp. 157–165, 2003.

[6] D. Gavalas, C. Konstantopoulos, K. Mastakas, and G. Pantziou, “Mobile recommender systems in tourism,” *Journal of Network and Computer Applications*, vol. 39, pp. 319–333, 2014.

[7] K. N. Rao and V. G. Talwar, “Application domain and functional classification of recommender systems—A survey,” *DESIDOC Journal of Library & Information Technology*, vol. 28, no. 3, pp. 17–35, 2008.

[8] X. Y. Su and T. M. Khoshgoftaar, “A survey of collaborative

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International Journal of Engineering Science and Advanced Technology (IJESAT)
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filtering techniques," *Advances in Artificial Intelligence*, vol. 2009, Article 421425, 2009.

[9] I. Cenamor, T. de la Rosa, S. Núñez, and D. Borrajo, "Planning for tourism routes using social networks," *Expert Systems with Applications*, vol. 69, pp. 1–9, 2017.

[10] G. Fenza, E. Fischetti, D. Furno, and V. Loia, "A hybrid context aware system for tourist guidance based on collaborative filtering," in *Proceedings of the IEEE International Conference on Fuzzy Systems*, Taipei, China, 2011, pp. 131–138.

[11] K. Meehan, T. Lunney, K. Curran, and A. McCaughey, "Context-aware intelligent recommendation system for tourism," in *2013 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops)*, San Diego, CA, USA, 2013, pp. 328–331.

[12] G. D. Abowd, A. K. Dey, P. J. Brown, N. Davies, M. Smith, and P. Steggles, "Towards a better understanding of context and context-awareness," in *Handheld and Ubiquitous Computing*, H. W. Gellersen, Ed. Berlin, Germany: Springer, 1999, pp. 304–307.

[13] O. Boulaalam, B. Aghoutane, D. El Ouadghiri, A. Moumen, and M. L. C. Malinine, "Proposal of a big data system based on the recommendation and profiling techniques for an intelligent management of Moroccan tourism," *Procedia Computer Science*, vol. 134, pp. 346–351, 2018.

[14] J. Borràs, A. Moreno, and A. Valls, "Intelligent tourism recommender systems: A survey," *Expert Systems with Applications*, vol. 41, no. 16, pp. 7370–7389, 2014.

[15] L. Ravi and S. Vairavasundaram, "A collaborative location based travel recommendation system through enhanced rating prediction for the group of users," *Computational Intelligence and Neuroscience*, vol. 2016, Article 1291358, 2016.

[16] K. H. Lim, J. Chan, C. Leckie, and S. Karunasekera, "Personalized tour recommendation based on user interests and points of interest visit durations," in *Proceedings of the 24th International Joint Conference on Artificial Intelligence*, Buenos Aires, Argentina, 2015, pp. 1778–1784.

[17] I. R. Brilhante, J. A. Macedo, F. M. Nardini, R. Perego, and C. Renso, "On planning sightseeing tours with TripBuilder," *Information Processing & Management*, vol. 51, no. 2, pp. 1–15, 2015.

[18] K. Al Fararni, B. Aghoutane, A. Yahyaouy, J. Riffi, A. Sabri, and A. Yahyaouy, "Comparative study on approaches of recommendation systems," in *Embedded Systems and Artificial Intelligence*, Fez, Morocco, 2019, pp. 753–764.

[19] P. Di Bitonto, M. Laterza, T. Roselli, and V. Rossano, "A recommendation system to promote local cultural heritage," *Journal of E-Learning and Knowledge Society*, vol. 7, no. 3, pp. 97–107, 2011.

[20] Z. Aarab, A. Elghazi, R. Saidi, and M. D. Rahmani, "Toward a smart tourism recommender system: Applied to Tangier city," in *Innovations in Smart Cities and Applications*, M. Ben Ahmed and A. Boudhir, Eds. Cham, Switzerland: Springer, 2018, pp. 643–651.

[21] J. P. Lucas, N. Luz, M. N. Moreno, R. Anacleto, A. A. Figueiredo, and C. Martins, "A hybrid recommendation approach for a tourism system," *Expert Systems with Applications*, vol. 40, no. 9, pp. 3532–3550, 2013.

[22] M. Hong, J. J. Jung, F. Piccialli, and A. Chianese, "Social recommendation service for cultural heritage," *Personal and Ubiquitous Computing*, vol. 21, no. 2, pp. 191–201, 2017.

[23] M. Vozalis and K. G. Margaritis, "On the enhancement of collaborative filtering by demographic data," *Web Intelligence and Agent Systems*, vol. 4, no. 2, pp. 117–138, 2006.

[24] A. T. Nguyen, N. Denos, and C. Berrut, "Exploitation des données 'disponibles à froid' pour améliorer le démarrage à froid dans les systèmes de filtrage d'information," in *Actes du XXIV Congrès d'INFORSID*, Hammamet, Tunisia, 2006, pp. 81–95.

[25] S. Kavitha, V. Jobi, and S. Rajeswari, "Tourism recommendation using social media profiles," in *Artificial Intelligence and Evolutionary Computations in Engineering Systems*, S. Dash, K. Vijayakumar, B. Panigrahi, and S. Das, Eds. 2017, pp. 243–253.

2250-3676 ijesatj@gmail.com https://www.ijesat.com/