International Journal of Contemporary Research in Computer Science and Technology (IJCRCST)
Volume 9, Special Issue 1 (April '2026)
ISSN: 2395-5325
Special Issue on International Conference on Innovation, Engineering & Management (ICIEM-2026)
Conference held at Garden City University, Bangalore, India.

PERSONALIZED RECOMMENDATION SYSTEM FOR TOURISM AND FOOD SERVICES USING HYBRID FILTERING

Niveditha Naik
MCA Student,
Department of Computer Science,
Garden City University, Bengaluru, India.

Abstract: *Personalization plays a key role in improving user satisfaction in digital platforms, especially within the tourism and food service sectors. Traditional recommendation systems often operate within a single domain, limiting their ability to provide comprehensive suggestions that match diverse user preferences. This paper proposes a personalized recommendation system for tourism and food services using a hybrid filtering approach that integrates collaborative filtering and content-based filtering techniques. The model analyzes user behavior, historical preferences, item attributes, and contextual factors such as location and time to generate accurate and relevant recommendations. The hybrid filtering method overcomes the limitations of individual techniques by combining similarity-based user patterns with feature-driven item analysis. Experimental results demonstrate enhanced precision and relevance in recommendations when compared with standalone models. The proposed system can be effectively implemented in travel platforms, food delivery applications, and tourism service aggregators to deliver a rich, personalized user experience.*

Keywords: *Recommendation System, Hybrid Filtering, Tourism, Food Services, Collaborative Filtering, Content-Based Filtering, Personalization*

I.INTRODUCTION

The rapid advancement of digital technologies and the widespread adoption of internet-based services have significantly transformed the tourism and food service industries. Modern users increasingly rely on online platforms and mobile applications to explore travel destinations, discover restaurants, and experience new cuisines. While this digital transformation has improved accessibility and convenience, it has also resulted in an overwhelming amount of information, making it difficult for users to make informed decisions. With thousands of destinations, hotels, restaurants, and food options available online, users often face the problem of information overload. Searching manually through multiple platforms can be time-consuming and inefficient, leading to confusion and dissatisfaction. As a result, there is a growing need for intelligent systems that can filter vast amounts of data and provide personalized recommendations tailored to individual preferences.

Recommendation systems have emerged as a powerful solution to address this challenge. These systems analyze user data, preferences, and behavior to suggest relevant items, thereby enhancing user experience and decision-making. In the context of tourism and food services, recommendation systems can help users discover destinations, restaurants, and cuisines that align with their interests, budget, and location. However, traditional recommendation approaches face several limitations that reduce their effectiveness.

Collaborative filtering, one of the most widely used recommendation techniques, relies on user interactions such as ratings and reviews to identify similarities between users. While effective in many scenarios, it suffers from issues such as the cold-start problem, where new users or items lack sufficient data for accurate recommendations. Additionally, data sparsity can lead to unreliable suggestions when user interactions are limited. On the other hand, content-based filtering focuses on the attributes of items, such as location, cuisine type, price range, and features. It recommends items similar to those the user has previously liked. Although this approach provides more control over recommendations, it often lacks diversity and fails to capture collective user preferences, resulting in repetitive suggestions.

To overcome these limitations, hybrid recommendation systems have been introduced, combining the strengths of both collaborative and content-based filtering techniques. By integrating multiple approaches, hybrid systems can deliver more accurate, diverse, and personalized recommendations while reducing the weaknesses of individual methods. In addition to filtering techniques, modern recommendation systems also consider contextual factors such as location, time, weather conditions, and user activity. For example, a user may prefer different types of restaurants during the day

IJCRCST © 2026 | All Rights Reserved

and night or choose travel destinations based on seasonal conditions. Incorporating such contextual information significantly improves the relevance and usefulness of recommendations.

This research proposes a **Personalized Recommendation System for Tourism and Food Services using Hybrid Filtering**, designed to provide intelligent and user-centric recommendations. The system analyzes user preferences, historical behavior, and contextual data to generate suggestions for tourist destinations and food services that best match individual needs. By leveraging hybrid filtering techniques, the system ensures a balance between personalization and diversity, delivering recommendations that are both relevant and varied.

The proposed system also integrates real-time data from external sources such as travel platforms, restaurant databases, and location-based services. This ensures that users receive up-to-date information, including ratings, reviews, and availability. Furthermore, the system incorporates a feedback mechanism that continuously learns from user interactions, improving recommendation accuracy over time. Another key aspect of this research is its focus on enhancing user experience and engagement. By providing tailored suggestions, the system reduces the effort required to search for suitable options and increases user satisfaction. For businesses in the tourism and food sectors, such systems offer opportunities to reach targeted audiences, improve customer retention, and increase revenue. The integration of machine learning techniques enables the system to adapt to changing user preferences and evolving market trends. As users interact with the system, it refines its recommendations, creating a dynamic and personalized experience. This adaptability is essential in industries like tourism and food services, where trends and user preferences frequently change.

The proposed hybrid recommendation system addresses the challenges of information overload, limited personalization, and inefficiencies in traditional systems. By combining advanced filtering techniques with contextual awareness and real-time data integration, the system aims to transform how users explore tourism and food services. It provides a scalable and efficient solution that benefits both users and service providers, contributing to the advancement of intelligent recommendation technologies.

II. OBJECTIVES

- To develop a personalized recommendation system for tourism and food services
- To implement a **hybrid filtering approach** combining collaborative and content-based methods
- To analyze user preferences, behavior, and contextual data
- To improve recommendation accuracy and relevance
- To overcome cold-start and sparsity problems
- To enhance user satisfaction and engagement

III. METHODOLOGY

The proposed **Personalized Recommendation System for Tourism and Food Services using Hybrid Filtering** follows a systematic and multi-stage methodology designed to ensure accurate, efficient, and personalized recommendations. The methodology integrates data collection, preprocessing, hybrid filtering techniques, and performance evaluation to create a robust recommendation framework. Each stage plays a crucial role in transforming raw data into meaningful suggestions tailored to individual user preferences.

A. Data Collection

The first stage of the methodology involves collecting comprehensive and diverse datasets required for generating meaningful recommendations. Data is gathered from multiple sources to ensure coverage of both tourism and food service domains. User-related data includes personal preferences, browsing history, ratings, reviews, and past interactions with the system. This information helps in understanding user behavior and identifying patterns in their choices.

In addition to user data, item-related data is collected, which includes details of tourist destinations such as location, type of attraction, popularity, cost, and user reviews. Similarly, food service data includes restaurant details, cuisine types, pricing, ratings, menus, and customer feedback. Contextual data such as user location, time of access, and seasonal factors may also be collected to improve recommendation relevance.

External data sources such as APIs from travel platforms, mapping services, and restaurant aggregators can be integrated to fetch real-time information. The combination of user, item, and contextual data forms a comprehensive dataset that enables the system to generate personalized and context-aware recommendations.

B. Data Preprocessing

The collected data is often unstructured and may contain inconsistencies, missing values, and noise. Therefore, a preprocessing stage is essential to ensure data quality and reliability. This stage begins with data cleaning, where duplicate records are removed and missing values are handled using appropriate techniques such as imputation or removal, depending on the significance of the data.

Next, data transformation is performed to convert raw data into a structured format suitable for analysis. Numerical values such as ratings are normalized to maintain consistency across different scales. Categorical data, such as cuisine types or location categories, are encoded using methods like one-hot encoding or label encoding.

Feature extraction and selection are also carried out in this stage to identify the most relevant attributes for recommendation. For example, features such as user preferences, frequently visited locations, and highly rated cuisines are prioritized. This reduces computational complexity and improves model efficiency.

By refining the dataset through preprocessing, the system ensures that the input data is accurate, consistent, and ready for effective model implementation.

C. Hybrid Filtering Approach

The core of the proposed system lies in the implementation of a hybrid filtering approach that combines collaborative filtering and content-based filtering techniques. This integration is designed to overcome the limitations of individual methods while enhancing overall recommendation accuracy.

Collaborative filtering analyzes user interactions such as ratings, clicks, and reviews to identify similarities between users or items. It operates on the assumption that users with similar preferences in the past will continue to have similar tastes in the future. Techniques such as user-based and item-based similarity measures are used to generate recommendations. However, collaborative filtering alone may struggle with new users or items due to insufficient data.

Content-based filtering, on the other hand, focuses on the attributes of items. It matches user preferences with item features such as destination type, cuisine category, or price range. This method is particularly useful for recommending items similar to those the user has previously liked. However, it may lack diversity and fail to incorporate broader user trends.

To address these challenges, the hybrid model combines both approaches using techniques such as weighted hybridization or switching mechanisms. In the weighted approach, outputs from both filtering methods are combined based on predefined weights, ensuring balanced recommendations. In switching methods, the system dynamically selects the appropriate technique depending on data availability. This hybrid strategy improves accuracy, reduces cold-start issues, and provides more diverse and relevant recommendations.

D. Recommendation Engine

The recommendation engine acts as the central component that processes preprocessed data and generates personalized suggestions. It integrates the outputs from the hybrid filtering model and applies ranking algorithms to prioritize the most relevant items for each user.

The engine evaluates multiple factors, including user preferences, similarity scores, contextual data, and popularity metrics, to produce a ranked list of recommendations. For tourism services, this may include destinations based on user interests, travel history, and seasonal relevance. For food services, the system recommends restaurants and cuisines based on taste preferences, location proximity, and user ratings.

Real-time processing capabilities allow the system to update recommendations dynamically as new data becomes available. For example, if a user provides new ratings or changes preferences, the system immediately adapts and refines its suggestions. Additionally, filtering mechanisms are applied to remove irrelevant or low-quality recommendations, ensuring that users receive only the most suitable options.

The recommendation engine thus transforms analytical outputs into actionable insights, providing users with a seamless and personalized experience.

E. Evaluation and Performance Metrics

The final stage of the methodology focuses on evaluating the effectiveness and performance of the recommendation system. Evaluation is conducted using both quantitative and qualitative metrics to ensure comprehensive analysis.

Quantitative evaluation involves measuring accuracy using metrics such as precision, recall, and F1-score. Precision evaluates the relevance of recommended items, while recall measures the system's ability to identify all relevant items. The F1-score provides a balanced measure of both precision and recall. These metrics help in assessing the quality of recommendations generated by the system.

In addition to accuracy metrics, user satisfaction is evaluated through feedback and surveys. Users are asked to rate the relevance, usefulness, and overall experience of the recommendations. This qualitative assessment provides insights into system usability and effectiveness from a user perspective. The system is also tested under different scenarios, including varying data sizes and user profiles, to evaluate scalability and robustness. Continuous monitoring and refinement are performed to improve system performance over time. Through comprehensive evaluation, the system ensures that it delivers reliable, accurate, and user-centric recommendations in real-world applications.

III. SYSTEM MODULES AND TOOLS

The AI-powered educational assistant is designed using a modular architecture, where each module performs a specific function while contributing to the overall learning ecosystem. This modular design ensures scalability, flexibility, and ease of integration of new features as technology evolves. The system consists of multiple interconnected components that collectively deliver a comprehensive learning experience.

Module	Key Tools & Technologies
Programming	Python
ML Libraries	Scikit-learn
Backend	Flask / Django
Frontend	HTML, CSS, JavaScript
Job Integration	LinkedIn API, RapidAPI, React, scikit-learn
Database	MySQL / MongoDB
API	Google Maps API, Travel APIs
Login & Home Page	HTML/CSS, Bootstrap, Firebase Auth, Django

Table 1. System Modules and Technologies

IV. RESULTS

The proposed **Personalized Recommendation System for Tourism and Food Services using Hybrid Filtering** was evaluated using a combination of user interaction data, simulated datasets, and real-time inputs to measure its effectiveness and performance. The evaluation focused on key aspects such as recommendation accuracy, personalization quality, system efficiency, and user satisfaction. The results demonstrate that the hybrid filtering approach significantly improves the overall performance compared to traditional single-method recommendation systems.

A.Recommendation Accuracy

One of the primary objectives of the system is to provide accurate and relevant recommendations to users. The hybrid filtering model was tested against individual collaborative filtering and content-based filtering approaches. The results indicate that the hybrid model achieved higher accuracy due to its ability to combine user behavior and item attributes effectively.

Precision and recall metrics were used to evaluate performance. The system showed a noticeable improvement in precision, meaning that a higher proportion of recommended items were relevant to user preferences. Similarly, recall values improved, indicating that the system was able to identify a larger number of relevant items from the dataset. The combined F1-score demonstrated balanced performance, confirming the effectiveness of the hybrid approach.

B. Personalization and Relevance

The system successfully delivered personalized recommendations tailored to individual user preferences. By analyzing user history, ratings, and contextual factors such as location and time, the system generated suggestions that closely matched user interests. For example, users who frequently interacted with budget-friendly restaurants received recommendations aligned with similar pricing categories, while users interested in luxury dining were presented with premium options. Similarly, in the tourism domain, users with a preference for adventure activities were recommended destinations such as trekking spots and nature reserves, whereas users interested in cultural experiences received suggestions related to heritage sites and museums. This level of personalization significantly improved the relevance of recommendations and enhanced user engagement with the system.

V. DISCUSSION

The experimental results demonstrate that the proposed **Hybrid Recommendation System** provides superior performance compared to traditional recommendation approaches that rely solely on collaborative filtering or content-based filtering. By integrating both techniques, the system effectively combines user behavioral patterns with item-specific characteristics, resulting in recommendations that are more accurate, diverse, and personalized. Collaborative filtering contributes by identifying similarities among users based on their historical interactions, ratings, and preferences, while content-based filtering analyzes item attributes such as destination type, cuisine, location, pricing, and popularity. The combination of these complementary techniques reduces the limitations associated with individual recommendation methods and enhances the overall recommendation quality.

One of the major strengths of the proposed system is its ability to address the **cold-start** and **data sparsity** problems that commonly affect recommendation systems. New users with limited interaction history can still receive relevant

IJCRCST © 2026 | All Rights Reserved

recommendations through content-based analysis, while users with rich historical data benefit from collaborative filtering. Furthermore, incorporating contextual information such as location, time, seasonal preferences, and user activity significantly improves recommendation relevance, enabling the system to adapt to different user situations.

The evaluation results also indicate improvements in **precision, recall, and F1-score**, demonstrating that the hybrid approach provides a better balance between recommendation accuracy and coverage. Personalized recommendations increase user engagement by reducing the effort required to search for suitable tourist destinations and restaurants. Businesses can also benefit from improved customer satisfaction, higher retention rates, and increased service utilization through targeted recommendations.

Despite these advantages, the effectiveness of the hybrid recommendation system is highly dependent on the quality, completeness, and availability of data. Inaccurate user profiles, incomplete ratings, outdated information, or inconsistent item descriptions may reduce recommendation accuracy. Therefore, continuous data collection, preprocessing, and model refinement are essential to maintain system performance. Overall, the proposed hybrid filtering framework provides a practical and scalable solution for intelligent tourism and food service recommendation systems.

VI. LIMITATIONS

Although the proposed Personalized Recommendation System demonstrates promising performance, several limitations should be considered before its practical deployment.

- **Requirement for Large Datasets:** The recommendation engine relies heavily on historical user interactions, ratings, browsing history, and item information. The availability of large, high-quality datasets significantly influences the accuracy of recommendations. When sufficient user interaction data is unavailable, particularly for new platforms, the recommendation quality may decrease.
- **Dependence on User Feedback:** Collaborative filtering techniques require continuous user feedback such as ratings, reviews, clicks, and browsing history to identify preference patterns. If users provide limited feedback or inconsistent ratings, the recommendation engine may struggle to accurately understand their interests, resulting in less personalized suggestions.
- **API Availability and External Dependencies:** The proposed system integrates information from external travel services, restaurant databases, mapping services, and location-based APIs. Any limitations in API availability, request quotas, pricing policies, or network connectivity may affect the real-time performance and reliability of recommendations. Changes made by third-party service providers may also require frequent system updates.
- **Privacy and Security Concerns:** Personalized recommendation systems require access to user information, including browsing history, location, preferences, and behavioral patterns. Collecting and processing such sensitive data raises important privacy and security concerns. Appropriate encryption techniques, user consent mechanisms, anonymization methods, and compliance with privacy regulations are essential to ensure responsible data management.
- **Cold-Start Challenges:** Although hybrid filtering reduces the cold-start problem, completely eliminating it remains difficult. New users with no interaction history and newly added destinations or restaurants may still receive less accurate recommendations until sufficient data becomes available.
- **Scalability Issues:** As the number of users, tourist destinations, restaurants, and reviews increases, computational complexity also grows. Maintaining real-time recommendation performance for millions of users requires efficient indexing, distributed computing, and scalable cloud-based infrastructure.

VII. FUTURE ENHANCEMENTS

The proposed recommendation system offers several opportunities for future improvement to further enhance recommendation quality, user experience, and scalability.

- **Mobile Application Integration:** Future versions of the system can be integrated with Android and iOS mobile applications, allowing users to receive personalized travel and restaurant recommendations directly on their smartphones. Mobile integration can also utilize GPS sensors to provide location-aware recommendations in real time.
- **Deep Learning-Based Recommendation Models:** Traditional hybrid filtering techniques can be enhanced using advanced deep learning models such as Neural Collaborative Filtering (NCF), Autoencoders, Graph Neural Networks (GNN), Transformer models, and Reinforcement Learning. These techniques can automatically learn complex user-item relationships and significantly improve recommendation accuracy.
- **Voice-Based Recommendation Services:** The integration of Natural Language Processing (NLP) and voice assistants can enable users to interact with the recommendation system using voice commands. Users

could simply ask for nearby restaurants or tourist attractions, making the system more accessible and convenient.

- **Real-Time Personalized Recommendations:** Future systems can continuously analyze live user interactions, browsing behavior, weather conditions, traffic information, and current events to dynamically update recommendations. Real-time personalization enables highly adaptive recommendations that reflect users' immediate needs.
- **Social Media Integration:** Incorporating user activities from social media platforms can provide additional insights into user interests, travel preferences, food habits, and lifestyle choices, resulting in richer user profiles and more personalized recommendations.
- **Explainable Recommendation Systems:** Future recommendation engines may include Explainable Artificial Intelligence (XAI) techniques that provide users with understandable explanations for why particular destinations or restaurants are recommended. Increased transparency improves user trust and system acceptance.
- **Multilingual and Cross-Domain Recommendations:** The system can be extended to support multiple languages and integrate additional recommendation domains such as hotels, transportation, entertainment, shopping, and local events, creating a comprehensive intelligent travel assistant.

IX. CONCLUSION

The proposed **Personalized Recommendation System for Tourism and Food Services using Hybrid Filtering** successfully demonstrates the effectiveness of combining collaborative filtering and content-based filtering techniques to generate accurate, relevant, and personalized recommendations. By analyzing user preferences, historical interactions, item attributes, and contextual information such as location and time, the hybrid model overcomes many of the limitations associated with traditional recommendation approaches, including cold-start problems and limited recommendation diversity. The experimental evaluation indicates that the hybrid recommendation framework improves recommendation precision, recall, personalization, and overall user satisfaction compared to standalone filtering methods. The integration of contextual information and real-time data further enhances the relevance of recommendations, allowing users to discover destinations, restaurants, and cuisines that closely match their individual interests. The system not only simplifies decision-making for users but also provides significant business benefits by increasing customer engagement, service utilization, and customer retention.

X. REFERENCES

[1]. Ricci, F., Rokach, L., & Shapira, B. (2022). *Recommender systems handbook* (3rd ed.). Springer.

[2]. Aggarwal, C. C. (2022). *Recommender systems: The textbook* (2nd ed.). Springer.

[3]. Zhang, S., Yao, L., Sun, A., & Tay, Y. (2021). Deep learning based recommender systems: A survey and new perspectives. *ACM Computing Surveys, 54*(1), 1–38.

[4]. Gao, C., Zheng, Y., Li, N., Li, Y., Qin, J., Piao, J., Quan, Y., & Chang, J. (2022). Graph neural networks for recommender systems: Challenges, methods, and directions. *ACM Transactions on Information Systems, 40*(3), 1–37.

[5]. Wu, L., He, X., Wang, X., Zhang, K., & Wang, M. (2022). A survey on neural recommendation: From collaborative filtering to content-based recommendation. *IEEE Transactions on Knowledge and Data Engineering, 34*(5), 2341–2365.

[6]. Sun, Z., Yang, J., Zhang, Y., Bozzon, A., & Zhang, J. (2021). Explainable recommender systems: A survey. *Foundations and Trends in Information Retrieval, 15*(4), 1–101.

[7]. Verbert, K., Ochoa, X., De Croon, R., Dourado, R., & Laenen, S. (2022). Context-aware recommendation systems: Recent developments and future directions. *User Modeling and User-Adapted Interaction, 32*(3), 451–492.

[8]. Chen, M., Li, Y., Wang, X., & Zhao, H. (2023). Hybrid recommendation systems using collaborative and content-based filtering: A comprehensive review. *Expert Systems with Applications, 213*, 118947.

[9]. Li, X., Wang, Z., & Chen, H. (2023). Personalized tourism recommendation using hybrid machine learning techniques. *Knowledge-Based Systems, 270*, 110523.

[10]. Sharma, P., Singh, R., & Gupta, V. (2023). Intelligent tourism recommendation using contextual information and user behavior analysis. *Journal of Hospitality and Tourism Technology, 14*(4), 621–639.

[11]. Kumar, A., Verma, S., & Patel, D. (2024). AI-driven personalized recommendation systems for smart tourism applications. *IEEE Access, 12*, 41762–41780.

[12]. Zhang, Y., Liu, H., & Wang, J. (2024). Deep learning approaches for personalized recommendation systems: Recent advances and applications. *Information Sciences, 668*, 120657.

[13]. Wang, T., Zhou, L., & Li, H. (2025). Real-time personalized recommendation using transformer-based neural networks. *Information Processing & Management, 62*(1), 104012.

[14]. Chen, Y., Kumar, S., & Patel, R. (2025). Hybrid deep learning recommendation framework for tourism and food service applications. *Expert Systems with Applications, 258*, 125114.