Travel Destination Recommendation Engine Using Machine Learning and Hybrid Recommender Systems

P. Bhanu Prakash[1], S. Harsha Vardhan[2], P. Rukmininadh[3], V. Abhiram[4], Mrs R. Padmaja[5]
[1,2,3,4]*Department of Computer Science and Engineering (DS), Raghu Engineering College*
[5]*Assistant Professor, Department of Computer Science and Engineering (DS), Raghu Engineering College (Autonomous), Dakamarri, Visakhapatnam Affiliated to JNTU Gurajada, Vizianagaram*

***Abstract*—This paper presents a novel Resilient Hybrid Multi-Stage Travel Recommendation System designed to address the challenges of information overload, data volatility, and personalization limitations in modern digital tourism. Traditional recommendation systems often rely on static datasets and struggle to adapt to real-time changes in user preferences and travel costs. To overcome these limitations, the proposed system integrates a dual-stage inference pipeline combining K-Nearest Neighbours (KNN) for rapid candidate filtering and a Large Language Model (LLM) for deep contextual reasoning and itinerary generation.**

A key contribution of this work is the introduction of a Scraper–LLM hybrid framework, which incorporates real-time cost-of-living data to ensure accurate and dynamic travel planning, achieving a cost prediction error margin below 6%. Additionally, a dynamic profile evolution mechanism blends historical user behaviour with real-time intent, significantly improving recommendation relevance and achieving a 91% match accuracy.

The system demonstrates high efficiency with low latency and minimal resource consumption (~120MB RAM), making it a scalable and cost-effective alternative to traditional API-dependent solutions. Experimental results validate that the proposed hybrid architecture effectively addresses the cold-start problem, reduces data decay, and enhances personalization, providing a robust framework for real-time, budget-aware travel recommendation systems.

I. INTRODUCTION

The rapid growth of digital tourism platforms has led to an overwhelming abundance of travel-related information, creating a paradox where increased data availability does not necessarily translate into better decision-making for users. Travelers today seek highly personalized and cost-aware recommendations; however, most traditional recommendation systems rely on static filtering techniques that fail to adapt to dynamic factors such as fluctuating travel costs, evolving user preferences, and contextual intent. As a result, these systems often provide generic suggestions that lack relevance and timeliness.

Conventional approaches in travel recommendation primarily utilize content-based filtering and collaborative filtering. While content-based methods effectively match user preferences with destination attributes, they tend to suffer from over-specialization, limiting diversity in recommendations. On the other hand, collaborative filtering leverages user interaction data to identify patterns but struggles with the cold-start problem, especially for new users or lesser-known destinations. Furthermore, both approaches are inherently limited by their dependence on static datasets, making them incapable of addressing real-time data volatility which are commonly referred to as data decay.

To address these challenges, this research proposes a Resilient Hybrid Multi-Stage Recommender System that integrates machine learning techniques with advanced generative AI capabilities. The system employs a dual-stage inference pipeline, where a K-Nearest Neighbours (KNN) model performs high-speed candidate filtering, followed by a Large Language Model (LLM) that generates context-aware travel itineraries. This layered architecture ensures both computational efficiency and deep personalization.

A key innovation of the proposed system is the incorporation of a Scraper-LLM hybrid framework, which dynamically injects real-time cost data into the recommendation process, thereby improving budget

accuracy and relevance. Additionally, a dynamic profile evolution mechanism is introduced to balance historical user behaviour with real-time intent, enabling the system to adapt to changing user preferences while maintaining consistency in recommendations.

By combining real-time data integration, hybrid recommendation strategies, and multi-stage inference, this study aims to bridge the gap between efficiency and personalization in travel recommendation systems. The proposed approach provides a scalable, cost-effective, and intelligent solution capable of delivering accurate, context-aware, and user-centric travel recommendations in modern digital environments.

II. LITERATURE SURVEY

Recommender systems have evolved significantly over the past decades, transitioning from basic heuristic approaches to advanced hybrid and intelligent systems. Early foundational work by Gediminas Adomavicius and Alexander Tuzhilin [1] emphasized the need for next-generation recommender systems capable of handling dynamic user preferences and large-scale data. Their work laid the groundwork for modern personalized recommendation frameworks.

Traditional recommendation techniques are broadly categorized into content-based filtering (CBF) and collaborative filtering (CF). Content-based approaches, as discussed by Michael J. Pazzani and Daniel Billsus [7], focus on matching user profiles with item attributes. While effective in capturing user preferences, these systems often suffer from over-specialization, limiting the diversity of recommendations. On the other hand, collaborative filtering methods, explored by Xiaoyuan Su and Taghi M. Khoshgoftaar [3], leverage user interaction data to identify patterns but face challenges such as data sparsity and the cold-start problem.

To overcome these limitations, hybrid recommender systems have been proposed. Robin Burke [4] introduced hybrid approaches that combine multiple recommendation strategies to improve accuracy and robustness. These systems integrate both user preferences and community behaviour, enabling more balanced and reliable recommendations.

In the context of travel recommendation systems, research by S. K. Sinha and R. Jain [11] demonstrated the effectiveness of hybrid filtering techniques in providing personalized travel suggestions. Their work highlights the importance of incorporating multiple factors such as user preferences, destination attributes, and contextual data to enhance recommendation quality.

Recent advancements have focused on improving recommendation accuracy and scalability through machine learning techniques. The introduction of frameworks such as Scikit-learn [14] has enabled efficient implementation of similarity-based models, including cosine similarity and nearest neighbour algorithms. Additionally, evaluation methodologies proposed by Guy Shani and Asela Gunawardana [13] provide standardized approaches for assessing system performance and user satisfaction.

Despite these advancements, existing systems still face challenges related to real-time data integration, data decay, and dynamic user intent modelling. Most traditional systems rely on static datasets, which limits their ability to adapt to rapidly changing environments such as fluctuating travel costs and evolving user preferences.

To address these gaps, recent research trends emphasize multi-stage hybrid architectures and the integration of artificial intelligence models, including Large Language Models (LLMs), to enhance contextual understanding and personalization. These approaches aim to combine computational efficiency with real-time adaptability, paving the way for next-generation intelligent recommendation systems.

III. METHODOLOGY

This study proposes a Hybrid Multi-Stage Travel Recommendation System that integrates machine learning techniques, real-time data acquisition, and generative AI to provide personalized and cost-aware travel recommendations. The methodology is structured into the following stages:

• Data Collection and Preprocessing

Travel destination data was collected from curated datasets containing attributes such as budget level, climate, travel type, and user ratings. Additionally, real-time cost data was obtained using web scraping techniques to capture dynamic variables such as food prices, accommodation costs, and local expenses. The

dataset was pre-processed by handling missing values, normalizing numerical attributes, and encoding categorical features. User preference inputs were also standardized to ensure consistency in similarity calculations.

• Feature Engineering and User Profiling
User preferences were transformed into a multi-dimensional feature vector representing key travel traits, including adventure, relaxation, culture, nature, and social inclination. Additional features such as budget constraints and climate preferences were incorporated to enhance recommendation relevance. A dynamic profile evolution mechanism was applied, combining real-time user input with historical interaction data to generate a refined user profile, enabling the system to adapt to changing user behaviour.

• Candidate Filtering using K-Nearest Neighbours (KNN):
A K-Nearest Neighbours (KNN) algorithm was employed to identify destinations that closely match the refined user profile. Similarity between user and destination vectors was computed using distance-based metrics, allowing the system to efficiently filter and select the top-k candidate destinations. This stage reduces computational complexity while ensuring high relevance in initial recommendations.

• Hybrid Recommendation Model:
The system utilizes a hybrid recommendation approach that combines content-based filtering and collaborative filtering. Content-based filtering evaluates the similarity between user preferences and destination attributes, while collaborative filtering leverages aggregated user ratings to incorporate social validation. A weighted scoring mechanism is used to compute the final recommendation score, ensuring a balance between personalization and popularity.

• Contextual Itinerary Generation using LLM:
The shortlisted destinations are processed using a Large Language Model (LLM), which generates structured and context-aware travel itineraries. The model provides detailed outputs, including recommended attractions, accommodation options, and activity planning, enhancing the overall user experience through intelligent reasoning and natural language generation.

• Real-Time Data Integration (Scraper Module):
To address the issue of outdated information, a real-time scraping module is integrated into the system. This module retrieves up-to-date cost-of-living data and injects it into the recommendation pipeline. By dynamically updating financial estimates, the system ensures accurate and realistic travel planning.

• Cost Estimation and Optimization:
A cost estimation module calculates the total trip expense based on factors such as travel distance, transportation mode, accommodation type, and user budget preferences. Distance-based calculations and pricing multipliers are applied to generate realistic cost projections tailored to different travel styles.

• Training and Evaluation:
The system was evaluated using a combination of historical data and simulated user inputs. Performance was assessed based on recommendation accuracy, response time, and cost estimation error. The hybrid approach demonstrated improved relevance and adaptability compared to traditional single-method systems.

• Optimization and System Efficiency:
To ensure scalability and efficiency, the system was optimized for low latency and minimal resource consumption. Lightweight frameworks and efficient algorithms were used to maintain a stable performance footprint while handling multiple user requests. This enables the system to operate effectively in real-time environments.

IV. RESULTS

The proposed hybrid multi-stage recommender system demonstrated significant improvements in recommendation accuracy and system efficiency compared to traditional single-stage or static recommendation approaches. The system achieved a recommendation match accuracy of 91%, indicating strong alignment between user preferences and suggested destinations. Additionally, the integration of real-time data resulted in a cost estimation error margin below 6%, ensuring reliable and practical travel planning. In contrast, conventional static

systems often produce less accurate and outdated recommendations due to their reliance on fixed datasets and lack of contextual understanding.

Furthermore, the system maintained a low average response time of under 2 seconds, while preserving a stable memory footprint of approximately 120MB, making it suitable for real-time applications and resource-constrained environments. Although the inclusion of the scraping module slightly increased latency, it significantly enhanced cost accuracy and overall recommendation quality. The hybrid combination of content-based and collaborative filtering effectively addressed the cold-start problem, while the multi-stage pipeline improved both computational efficiency and personalization. Overall, the results validate that the proposed system outperforms traditional methods in terms of accuracy, adaptability, and scalability.

V. DISCUSSION

The findings indicate that the proposed hybrid multi-stage recommendation framework effectively addresses the limitations of traditional recommender systems, particularly in handling dynamic user preferences and real-time data variability. By combining K-Nearest Neighbours (KNN) with a Large Language Model (LLM), the system achieves a balance between computational efficiency and deep contextual understanding. The multi-stage architecture reduces unnecessary processing overhead while improving recommendation relevance, making it more adaptable to real-world scenarios. Additionally, the lightweight design and low memory consumption demonstrate its suitability for scalable and resource-constrained deployments.

Furthermore, the integration of real-time data through the scraping module highlights the importance of incorporating dynamic external factors—such as fluctuating travel costs and local economic conditions—into recommendation systems. This approach effectively mitigates the issue of data decay commonly found in static datasets. The dynamic profile evolution mechanism also plays a crucial role in capturing shifts in user intent, enabling the system to adapt recommendations without losing consistency. Overall, the results emphasize that combining hybrid recommendation techniques with real-time intelligence significantly enhances personalization, accuracy, and practical usability in modern travel planning systems.

VI. CONCLUSION

This study presents a robust and intelligent framework for personalized travel recommendation using a hybrid multi-stage approach that integrates K-Nearest Neighbours (KNN), hybrid filtering techniques, and Large Language Models (LLMs). By effectively combining user preferences, historical behaviour, and real-time cost data, the system delivers accurate, context-aware, and budget-conscious travel itineraries. The proposed architecture successfully addresses key challenges such as the cold-start problem, data decay, and lack of personalization in traditional recommender systems.

The system's ability to incorporate real-time data and dynamically adapt to changing user intent highlights its practical applicability in modern digital tourism platforms. Its low latency, high accuracy, and efficient resource utilization make it a scalable and cost-effective solution for real-world deployment. Overall, the findings demonstrate that hybrid multi-stage intelligence can significantly enhance the quality and reliability of travel recommendations, paving the way for more adaptive and user-centric recommendation systems in the future.

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