EXPLOREIT : Itinerary Generator

Mayank Misal[1], Mohit Kapgate[2], Om Patle[3], Kunal Lanje[4], Prof. Mrunali Chore[5]

[1]Student, Computer Science & Engineering, Priyadarshini College of Engineering, Nagpur
[2]Student, Computer Science & Engineering, Priyadarshini College of Engineering, Nagpur
[3]Student, Computer Science & Engineering, Priyadarshini College of Engineering, Nagpur
[4]Student, Computer Science & Engineering, Priyadarshini College of Engineering, Nagpur
[5]Assistant Professor, Computer Science & Engineering, Priyadarshini College of Engineering, Nagpur

---***---

Abstract - Trip planning can be challenging due to the large amount of travel information available in online, including destinations, transportation, and activities. Many Pre-existing travel planning tools provide general Suggestions that do not fully consider Individual entity user preferences. To Mitigate this limitation, This study introduces an **EXPLOREIT**, an intelligent system designed to generate personalized travel itineraries using Large Language Models (LLMs) and artificial intelligence techniques. The developed model analyses user inputs such as preferred destinations, travel dates, budget constraints, interests, and trip duration to produce customized travel plans. By integrating A chatbot with recommendation features, the system can suggest suitable attractions, accommodation options, and travel routes that align with the user's preferences. Not only that, the platform can Make use of travel-related data such as reviews, ratings, and cost details to enhance the accuracy and usefulness of suggestions. The AI-powered planner works as a web or mobile app that makes trip planning easier for travelers and reduces the time they spend searching and organizing everything on their own. The results indicate that integrating LLM technology into travel planning systems can significantly enhance personalization, improve decision-making, and deliver a seamless and engaging trip planning experience for users.

Key Words : Travel planner; Large Language Model; Recommender system; Customized itinerary; Travel guide system.

1.INTRODUCTION

In recent years, tourism has grown into one of the largest and fastest-growing service industries, supported by the rapid expansion of online platforms that provide information about destinations, transport, accommodation, and activities. Still, for most travelers, planning a trip remains a complex, time-consuming task and requires manually browsing on different websites, By comparing scattered information and organizing it into a clear itinerary that suits the budget, time, and personal interests. Traditional tour packages and many existing recommendation systems often deliver generic suggestions that fail to capture the variations of individual preferences.

Recent advances in artificial intelligence (AI), especially large language models (LLMs) and conversational agents, help make travel planning smarter, more interactive, and more personal. At the same time, there have been advances in recommender systems and data-driven tourism platforms show that incorporating user ratings, emotional responses, and behavioral patterns can significantly improve the relevance of suggested points of interest.

Many AI-based travel tools still rely on static or outdated data, reducing their ability to show real-time destination and hotel availability, pricing, and constraints . Moreover, conventional LLM applications in travel planning struggle with issues like the cold-start problem, where the system has little data for new users, maintaining consistent preferences across multiple interactions, and ensuring logical, feasible itineraries over several days .

So, there is a need for a travel planning system that combines everything in one place. that combines the natural-language capabilities of LLMs with real-time, data-driven recommendation and robust personalization mechanisms. Such a system should be able to collect user requirements through conversation, access up-to-date travel data, plan multi-day trips that are practical and achievable , and adapt to user feedback over time. The aim of this research is to design and develop an LLM-based intelligent travel planner that solves these gaps by bringing everything together conversational interaction, web-scraped real-time information, and personalized recommendation into a single, user-centric platform.

2. PROBLEM STATEMENT

Although AI-driven trip planners are becoming more common, travelers still lack a unified system that can generate accurate, validate, and adapt multi-day itineraries aligned with their evolving preferences and constraints. Current tourism advice platforms and packaged solutions offer pre-planned routes and fixed options that rarely account for individual ratings, emotions, and diverse exploration patterns, which leads to less appropriate destination selections and experiences . Users are therefore forced to manually integrate information about attractions, transportation, and accommodation from different sources, despite evidence that they prefer a single consolidated resource for destination information .

LLM-based planners have started to reduce the burden of manual planning by generating itineraries from natural-language descriptions of user needs, but they face major limitations. Traditional LLM setups in travel domains are limited by high cost involved in fine-tuning, cold-start challenges when user data is limited, difficulties in ensuring the itinerary is practical and feasible, and insufficient mechanisms for maintaining contextual memory across multi-turn interactions . As a result, generated plans may overlook budget limits, area-specific limits, or user-specific patterns, and may not remain consistent when users refine their preferences over several conversations.

Another issue is that real-time information is not fully used, different types of data in many existing tools. While some systems already scrape flight and hotel information and use content-based recommendation engines, their focus is primarily on matching prices, ratings, and preferences for layovers, rather than on integrating these constraints with long-horizon reasoning about daily timings and travel speed. Moreover, very few platforms maintain easy to understand, persistent user models that accumulate knowledge across trips to address cold-start and improve personalized experience over time.

3. OBJECTIVE

Our object of this project is to develop a automated travel planning platform based on AI so that it delivers accurate, feasible and personalized itineraries through combination of information accessed by user, recommendation techniques, real time data integration and several constraints based upon preferences.

First step is the designing of chatting interface where we will gather formalized preferences from the user in natural language such as destination, budget, number of travelers, interest and all this will be structured into requirements to generate an itinerary. Considering real world scenario and capturing the user choices through prompt engineering, this would help in refinement of plans and generate step by step.

Second step will integrate this information and integrate reasoning for enhanced itinerary planner based on LLMs, capable of decomposing this user goals into subtasks and classifying them as attraction scheduling, transport planning and accommodation suggestion. Building on ideas to incorporate other factors such as geography , culture, budget constraints and refine multi-day itineraries for feasibility.

Third step of the project will be data driven recommendation layer that uses APIs based on travel data such as flights, hotels, weather, local prices to implement according to user constraints and preferences, similar to content-based engines that match budgets, ratings, layovers. This layer will be tightly coupled with LLM so that itineraries are grounded and realistic to implement.

Fourth step of project brings us to the consistent and interpretable module of the system that is memory module that stores and updates user profile from time to time based on preferences , feedback, interaction history and addressing cold start limitations improving the long-term personalization in line with recent framework based upon memory management.

Finally, the project will help to analyze and generate the itinerary based upon quantitative and qualitative measures such as precision, ratings, satisfaction of user, usability and following this that validates the recommendations through different information accessed and also by analyzing users usage with other tools as well.

4. SCOPE OF PROJECT

The scope of project is defined in a way so that is focus on end-to-end planning and personalization for individual leisure travelers, while leaving out several complex functionalities which involves bookings, social companion matching and that traditional research . This system is designed to address this core trip planning based on destination, multiday itinerary generation and recommendation of transport and accommodation options within user specific budget .

It concentrates on short to medium trips rather than long relocation and will primarily target domestic or well-documented generation of itinerary where the destinations are mentioned and data can be found easily upon web so integrate and generate a well-planned route.

On the technological domain project includes a web-based front end and backend coordinates with LLM interaction and data retrieval upon the integration of one or more external data providers including the hotels reviews, destination reviews and weather forecasting and other available data consistent and prior data driven approaches helps to run the module and gather content based upon the updated information. The project will also implement basic user memory to store preferences , past trips and feedbacks providing a full large scale agent developed.

Certain functionalities such as integrated payments, guaranteed booking are out of this scope and will provide links to external applications offering these services so that user might check and make it work, similarly highly specialized domains like such as risk adventure and travel visa consulting or legal compliance are considered beyond projects boundary.

Evaluation will be conducted with the controlled group of users with predefined test scenarios rather than at global production scale with users, predefined test scenarios. With these boundaries, the project aims to deliver a robust system that demonstrates how LLM based reasoning, data driven recommendation and persistent personalization can be helpful in enhancing digital travel planning.

5. METHODOLOGY

The proposed **EXPLOREIT** is designed to generate personalized travel itineraries by combining Artificial Intelligence, Large Language Models (LLMs), and recommendation system techniques. The methodology follows a structured process that includes data collection, data preprocessing, itinerary generation, recommendation modelling, user interface development, and system evaluation. Each stage of the methodology is described below.

5.1 Gathering user input

The first stage of the system involves collecting travel preferences from users through a user-friendly interface. users share key information such as the starting location, destination, travel duration, number of travellers, budget, and preferred activities. To assist users in selecting locations efficiently, a feature that suggests places as you type, using location APIs (such as Google Places API) can be used. This functionality dynamically suggests possible locations as the user types, improving both accuracy and usability.

The collected inputs act as the primary parameters for generating customized travel itineraries. These parameters help the system understand the traveler's preferences and constraints, which are then used in later stages of the recommendation process.

5.2 Itinerary Generation Using LLM

In the second stage, the system utilizes a Large Language Model (LLM) through an API to generate personalized travel itineraries. The model analyses the user's travel requirements and provide structured travel suggestions.

To achieve effective results, prompt engineering techniques are applied. Prompt engineering involves designing well-structured prompts that guide the LLM to generate accurate and meaningful outputs. The prompts include information such as the destination, number of travel days, budget range, preferred attractions, and activity. The LLM processes the prompt and generates detailed itinerary suggestions, including recommended tourist attractions, and daily travel plans. The output is then analyzed and organized into a structured itinerary that users can easily understand.

5.3 Data Collection

To keep the system's travel info accurate and current, it pulls data from all kinds of sources flights, hotels, tourist spots, and prices. It grabs this info using APIs or web scraping tools, grabbing what it needs straight from travel websites. The collected data typically includes attributes such as airline details, flight duration, hotel ratings, accommodation prices, facilities, and customer reviews. This information enables the system to generate realistic travel recommendations that match the user's preferences and budget constraints.

5.4 Data Preprocessing

After gathering the data, the next step is to clean it up and get it into shape so it actually works well. This means rolling up your sleeves for a few things: getting rid of duplicates, tossing out anything irrelevant, fixing weird formatting, and making sure everything lines up. If there are missing values, you deal with them, whether that means filling in gaps or just cutting them out. For numbers like prices or ratings, you use normalization, so they actually make sense next to each other. By the end of all this, the data's clean, organized, and ready for the recommendation engine to use.

5.5 Recommendation Engine Development

This system uses a content-based recommendation engine to help people find travel options they actually want. It checks out the details for each travel item like where it is, how much it costs, hotel ratings, amenities, and how long it takes to get there and matches those details with what users say they're looking for.

Every travel option gets its own profile, a sort of digital snapshot with all these features. Then, the engine uses things like cosine similarity and TF-IDF to see how closely each option matches what the user likes.

By comparing these profiles, the system figures out which hotels, attractions, or flights fit someone's preferences and budget. So, users end up with recommendations that actually make sense for them.

5.6 Design of User Interfaces

In order to facilitate seamless user-system interaction, the user interface is essential. Modern web frameworks and technologies are used to create a web-based interface that offers interactive and responsive user experience.

The interface allows users to input travel preferences, view generated itineraries, and explore recommended travel options. The system presents results in a clear format that may include day-wise travel schedules, attraction descriptions, estimated costs, and map-based navigation. This design improves usability and helps travelers easily understand their travel plans.

5.7 Performance Evaluation

To really know if the recommendation system does its job, we have to check how solid its suggestions are. Here's how it goes: first, we split the data some goes into training, the rest into testing. That way, we see how the system deals with options it hasn't run into before.

Precision's easy to get. It measures if the system recommends travel choices that matter to people. We look at how many of its picks match what users like, based on the test data. Then we figure out what percentage of its recommendations were right. That number gives us a clear idea of whether the system's heading in the right direction.

6. RESULT

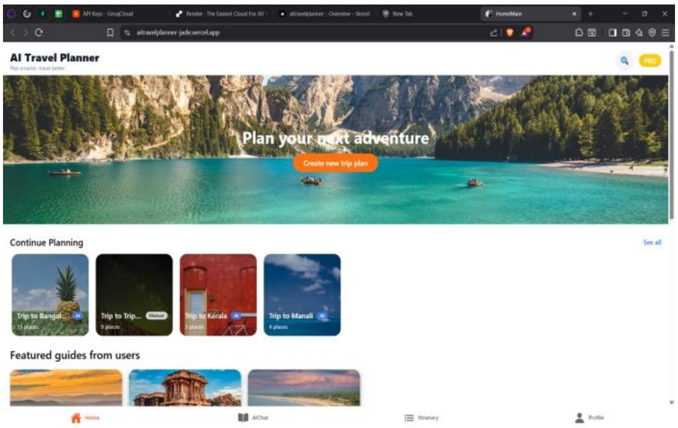

Fig-1 Home Page

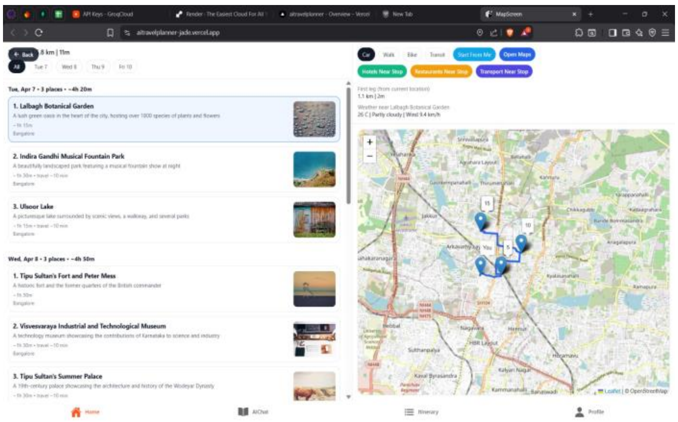

Fig -2 Itinerary

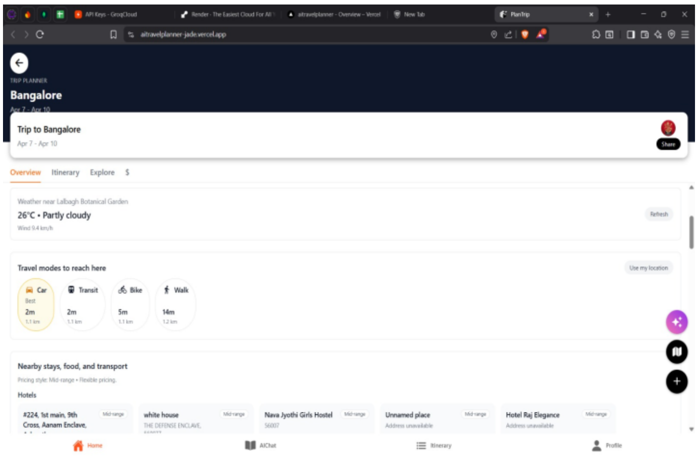

Fig 3: AI Trip Assistant

7. CONCLUSIONS

In conclusion, the proposed LLM-based travel planner shows that combining conversational AI, real-time data integration, and personalized recommendation techniques can significantly improve the quality, ease of use, and personalization of trip planning compared with the tools typically used. Systems that combine a content-based recommendation engine with chat-based preference gathering have already demonstrated the ability to produce accurate, personalized itineraries and go beyond current technologies in terms of accuracy and user pleasure.

By adding a personalisation layer with memory support and structured planning logic, such systems can further enhance cold-start performance, practicality of the itinerary, and long-term consistency in multi-turn interactions.

Overall, the project aligns with current research trends showing that AI-powered travel platforms improve planning efficiency , minimize user effort also enhancing the travel experience with personalized recommendations, better match with user preferences, and guidance for the entire journey

Future work can build on this foundation by expanding data sources, integrating direct booking, and utilising more detailed user feedback and social features to deliver even more adaptive, personalised travel support.

REFERENCES

[1] Y. Zhai, X. Wei, and J. Song, "Design and implementation of a personalized tourism recommendation system based on data mining and collaborative filtering algorithms," *Complexity*, vol. 2020, pp. 1–13, 2020.

[2] M. Chen, B. Zhang, and J. Zhang, "Personalized travel recommendation system based on social media data and machine learning algorithms," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, no. 4, pp. 1367–1376, 2019.

[3] A. Kontogianni, E. Alepis, and C. Patsakis, "Promoting smart tourism personalised services via a combination of deep learning techniques," *Expert Systems with Applications*, vol. 187, Article 115964, 2022.

[4] Q. Wang and D. Tang, "Research on intelligent recommendation business model of tourism enterprise value platform from the perspective of value co-creation," *Complexity*, 2021, Article ID 8441844.

[5] F. Santos, A. Almeida, C. Martins, R. Gonçalves, and J. Martins, "Using POI functionality and accessibility levels for delivering personalized tourism recommendations," *Computers, Environment and Urban Systems*, vol. 77, Article 101173, 2019.

[6] S. Du, H. Zhang, H. Xu, J. Yang, and O. Tu, "To make travel healthier: A new tourism personalized route recommendation algorithm," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, no. 9, pp. 3551–3562, 2019.

[7] E. Park, J. Park, and M. Hu, "Tourism demand forecasting with online news data mining," *Annals of Tourism Research*, vol. 90, Article 103273, 2021.

[8] C. Bin, T. Gu, Y. Sun, and L. Chang, "A personalized POI route recommendation system based on heterogeneous tourism data and sequential pattern mining," *Multimedia Tools and Applications*, vol. 78, no. 24, pp. 35135–35156, 2019.