International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 4S, 2025
https://www.theaspd.com/ijes.php

Trip Tailor: AI-Powered Travel Planning with Itinerary Generation and Chatbot Assistance

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Abstract: AI-driven travel planning systems, such as those using ChatGPT and content-based recommendation engines have shown promise in itinerary generation but often lack real-time adaptability and retrieval-augmented mechanisms. This limits their ability to provide dynamic, context-aware recommendations. The proposed work introduces an AI-powered system that streamlines travel planning with tailored itinerary generation and real-time travel assistance. The itinerary generator, powered by Google Generative AI (Gemini API), creates custom travel plans based on user inputs like destination, duration, budget, and companions. Integrated with the Google Places API, it provides detailed recommendations for hotels and day-by-day itineraries, including optimal timings, travel durations, and ticket pricing. The travel assistant chatbot, utilizing a RAG pipeline with the Deep Seek-R1 model, offers real-time, conversational insights through Wikipedia API data. FAISS-based indexing ensures fast, accurate responses, supported by pre-processing techniques like text normalization and entity extraction. This dual-component system delivers a scalable and user-friendly solution, combining generative AI with robust retrieval mechanisms to meet the growing demand for personalized and adaptable travel planning.

Keywords: AI-driven travel planning; Itinerary generation; RAG pipeline; Google Gemini API; Google Places API; DeepSeek-R1; FAISS indexing; Text normalization; Entity extraction; Conversational AI

1. INTRODUCTION

Tourism is one of the fastest-growing industries worldwide, significantly contributing to the global economy [1]. With the rapid evolution of technology, the way people plan their trips has shifted from traditional guidebooks and travel agencies to digital platforms that offer dynamic and personalized recommendations [3]. The integration of artificial intelligence (AI) and data-driven approaches has further revolutionized the travel industry by enabling intelligent, tailored, and efficient planning experiences [2][5]. However, despite these advancements, many existing systems still lack real-time adaptability and fail to provide context-aware suggestions, making the process of travel planning cumbersome and time-consuming [3].

Planning a trip requires comprehensive research—selecting destinations, accommodations, activities, and estimating expenses. Travelers often rely on multiple, disjointed sources to gather information, which can be overwhelming and lead to decision fatigue [2]. Moreover, itinerary planning demands consideration of various factors such as travel time, budget constraints, and the availability of attractions, making it a multifaceted task. While traditional travel agencies offer pre-structured packages, they are often expensive and lack the flexibility to cater to individual preferences [4]. Given the growing demand for customized travel experiences, there is an evident need for intelligent systems that streamline itinerary creation while supporting adaptability and real-time assistance [5].

To address these challenges, this project introduces an AI-powered travel planning system that automates and enhances itinerary generation using advanced machine learning techniques [5][6]. The itinerary generator utilizes Google's Generative AI (Gemini API) to create personalized plans tailored to user preferences such as destination, travel duration, budget, and companions. Through integration with the Google Places API, the system provides detailed suggestions for accommodations, attractions, and activities—along with optimal visiting times, estimated durations, and cost predictions [3][6]. Additionally, a travel assistant chatbot is implemented using a Retrieval-Augmented Generation (RAG) pipeline powered by the Deep Seek-R1 model. This chatbot interacts with users in real time, drawing contextual insights from the Wikipedia API, and leverages FAISS-based indexing alongside preprocessing techniques like text normalization and entity extraction to ensure fast and accurate responses [6].
The inclusion of a chatbot not only enhances itinerary planning but also offers historical and contextual information about destinations, enriching the travelers overall experience [5]. Its ability to dynamically retrieve and generate relevant insights ensures that users receive comprehensive, timely, and personalized support tailored to their interests [6]. By combining generative AI with retrieval-based mechanisms, this project presents a scalable, user-centric solution that bridges the gap in traditional travel planning, delivering an enhanced, context-aware, and adaptive travel experience [5][6].
This research paper explores the development of an AI-powered travel planning system, organized into key sections for clarity. The abstract introduces a dual-component system using Google Generative AI and a RAG-based chatbot to address the limitations of current AI travel tools. The introduction discusses the demand for personalized travel and issues with traditional planning. The literature review examines existing tools like ChatGPT and content-based recommenders, noting their lack of real-time adaptability. The methodology outlines system integration with Gemini API and Deep Seek-R1, supported by FAISS retrieval. Tables and graphs present performance metrics and user feedback. The results confirm the system's ability to deliver tailored, adaptable itineraries, and the conclusion highlights its value in modern travel planning, with all sections backed by credible references.

2. LITERATURE

Tourism recommendation systems have significantly evolved, leveraging various techniques to improve user experiences and deliver personalized travel suggestions. A content-based recommendation engine has been developed to match possible travel outcomes with a traveler's budget and priorities, ensuring more relevant recommendations [1]. Additionally, user-enhanced profiles have been explored, where recommendations are generated based on basic user data, relationships with stereotypes, and different functionality levels [2]. To improve computational efficiency in large-scale data processing, knowledge-based transfer learning has been applied to reduce delays and enhance model performance [3].

The COVID-19 pandemic drastically impacted the global tourism sector, transforming once overcrowded destinations into empty spaces. This situation underscored the need for adaptable tourism recommendation systems that consider external factors like travel restrictions and public health concerns [4]. One approach to tackling this challenge involves utilizing network crawlers to capture and preprocess travel-related text data, such as segmenting and filtering irrelevant content, to create standardized datasets for further analysis [5]. Moreover, discourse analysis has been incorporated into tourism demand forecasting, helping destinations address externalities influenced by media coverage and evolving traveler preferences [6].

Designing an efficient itinerary recommendation system is complex due to multiple real-world constraints, such as limited touring time, unpredictable traffic, weather fluctuations, group travel dynamics, queue times, and crowdedness at major tourist spots [7]. Optimization techniques have been implemented to determine the most efficient travel routes based on user-defined parameters like time constraints, starting points, and preferred destinations [8].
Furthermore, systems have been designed to facilitate the exploration of heritage sites, offering tourists deeper insights into historical and cultural landmarks [9].

Social media has emerged as a crucial component of travel decision-making, with platforms like TripAdvisor being highly trusted sources of travel information [11]. Future enhancements in travel planners could involve real-time updates, optimized booking systems, and advanced data analytics for personalized recommendations [14].

Additionally, Artificial Neural Networks (ANNs) have been explored for travel time estimation, proving to be effective in providing precise predictions with limited input data [15].

Building upon these developments, this paper proposes an AI-driven itinerary generator utilizing Gemini AI for dynamic and intelligent travel planning. The system processes user prompt inputs to generate optimized travel schedules, incorporating real-time factors such as weather conditions, crowd density, and available transportation options to enhance recommendations. Additionally, this project features a chatbot module that provides historical insights about travel destinations, enriching the overall user experience. By integrating AIpowered itinerary planning with an intelligent conversational assistant, this research aims to revolutionize personalized travel recommendations, offering seamless and data-driven exploration opportunities for travelers.

3. Methodology

This section outlines the detailed methodology used to develop and implement the **AIpowered travel planning system**. The system consists of two main components: the **Itinerary Generator** and the **Travel Assistance Chatbot**. Each component is described in detail, highlighting the **AI models, data sources, and techniques** employed. The methodology follows a structured pipeline to ensure accurate, efficient, and user-friendly travel planning.

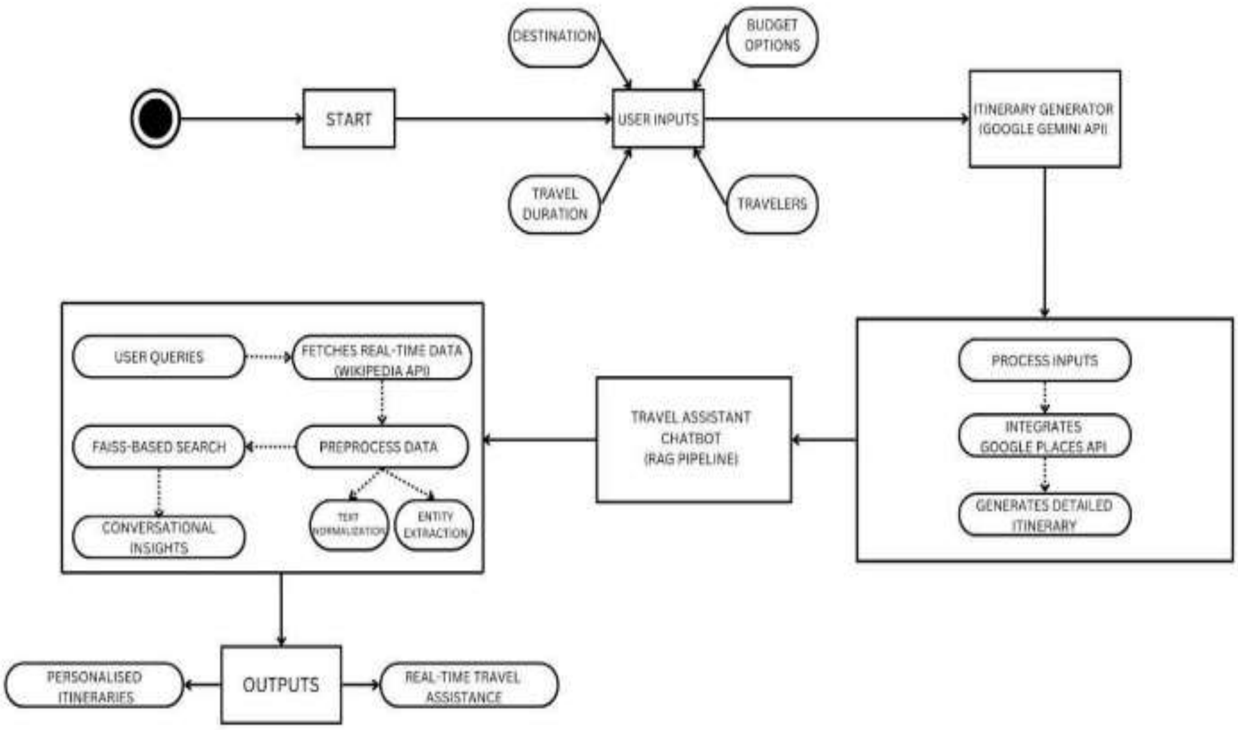

Fig 1 : System Architecture : Flowchart of an AI-powered travel planning system

3.1 Stage 1: User Input

The system first collects input from the user, including:

Destination preferences (e.g., city, region, or country), allowing users to specify multiple locations of interest.
Duration of the trip (e.g., number of days), ensuring the itinerary is structured effectively.
Budget (e.g., total expenditure available for travel), used to filter options within an affordable range.
Number of travelers (e.g., solo, couple, group), impacting accommodation and activity suggestions.
Special interests (e.g., adventure, culture, relaxation), ensuring recommendations match personal preferences.
The input data is parsed using **Natural Language Understanding** (NLU) within **Google Gemini AI**. The model tokenizes and encodes the query to **extract structured preferences**, incorporating real-time contextual factors such as weather, attraction availability, and current travel restrictions.

3.2 Stage 2: Data Integration and Retrieval

To provide **accurate** and **up-to-date** recommendations, the system integrates multiple APIs and data sources. The **Google Places API** is utilized to fetch:

Hotels (availability, ratings, pricing) to recommend accommodations that fit user preferences.
Tourist attractions (historical sites, landmarks, parks) ensuring the best local experiences.
Restaurants and services (cuisine, transport options) to optimize dining and mobility choices.
The retrieved data is **indexed and structured** for efficient access by the itinerary generator, ensuring real-time and location-aware recommendations.

3.3 Stage 3: Data Preprocessing

To prepare data for recommendation, preprocessing includes:
Data Cleaning: Removing duplicates, correcting inconsistencies, and standardizing text formats.
Standardization: Formatting dates, prices, and addresses uniformly to maintain consistency.
Handling Missing Data: Using **mean imputation** for numerical data or removing incomplete records for categorical data.
Feature Scaling (Normalization): Ensuring numerical attributes like ratings and cost are on the same scale:

$$X' = (X - X_{min})/(X_{max} - X_{min}) \quad \rightarrow \text{eq.1}$$

Vector Representation: Converting data into structured feature embeddings for efficient retrieval.

3.4 Stage 4: Itinerary Generation

3.4.1 Tourist Attraction Recommendation – k-Nearest Neighbors (k-NN)

The system **recommends places** using the **k-NN algorithm**, which finds **k** similar attractions based on user preferences.
Steps :
1. **Feature Vector Representation:** Each attraction is represented as a feature vector:

$$P_i = [C_{i,} R_{i,} D_{i,} P_i] \quad \rightarrow \text{eq.2}$$

Where

C_i = category (adventure,cultural, etc)
R_i = rating score
D_i = distance from user's location
P_i = popularity score

where **feature vectors** are places.
Top-k Selection & Filtering:
Returns **k nearest** places based on similarity ranking.
Filters recommendations based on **budget constraints and travel time**.

3.4.2 Route Optimization – Genetic Algorithm (GA)

To **find the optimal visiting order** for attractions, the system applies **Genetic Algorithm (GA)**.
Steps:
Chromosome Representation:
Each chromosome represents an **ordered list** of attractions.

Fitness Function:

$$f(C) = \sum_{\{i=1\}}^{\{n-1\}} d(Pi, P\{i+1\}) \quad \rightarrow \text{eq. 3}$$

Evaluates total travel time
d(Pi+Pi+1) is the distance between two locations.
Selection Mechanism:
Roulette Wheel Selection or Tournament Selection used to pick the best candidates.

3. **Crossover Operator:** Uses Partially Mapped Crossover (PMX) to combine two parent itineraries.
4. **Mutation Operator:** Randomly swaps two attractions to add variation.
5. **Convergence Criterion:** Stops when fitness levels off or max iterations are reached.

This method **ensures an optimized** and **efficient** route planning for travelers.

3.5 Stage 5: Retrieval-Augmented Generation (RAG) for Travel Assistance

The chatbot enhances responses using **RAG**, combining **retrieval-based search** with **LLM generation**.

3.5.1 Knowledge Base Construction

1. **Building the FAISS Index:**

Converts **textual travel data** into high-dimensional vectors. Uses **FastText embeddings** to map text into vector space.
The database stores these embeddings for **fast similarity search**.

3.5.2 RAG-Based Retrieval – FAISS (Facebook AI Similarity Search)

The chatbot **retrieves relevant information** from a **pre-built vector database** before generating responses.
Steps:
Vectorizing User Query Q
Converts query into an embedding vector .Vq

FAISS Search (Nearest Neighbor Retrieval) o Finds D_k **similar documents** using **L2 Distance**:

$$d(A,B) = \sqrt{\sum_{i=1}^{n}(A_i - B_i)^2} \quad \rightarrow \text{eq.4}$$

Where A, B and are **embedding vectors**.
Weighted Ranking: Assigns a score based on similarity and source reliability.

Response Augmentation:
o Retrieved content is passed to an **LLM** (e.g., DeepSeek-R1) to **generate a humanlike response**.

3.5.3 Real-Time Wikipedia Fetching

For **new or less-known destinations**, the system fetches **real-time information** from **Wikipedia**.

Steps:
1. **Query Classification:**

If retrieval fails, calls Wikipedia API

2. **API Data Processing:**

Extracts summary paragraphs related to query.

International Journal of Environmental Sciences
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3. FINAL RESPONSE GENERATION:

Wikipedia data is **merged** with FAISS retrieval to **generate a final, enriched response**.

4. RESULTS AND EVALUATION

The performance of the AI-powered travel assistance chatbot was evaluated using a combination of objective metrics and user feedback. This section presents the evaluation results, comparing them with traditional travel recommendation systems. The chatbot's efficiency was assessed using relevance-based metrics such as BLEU, ROUGE, and Recall@K, while user experience was analyzed through a Likert-scale survey.

The chatbot's performance was evaluated using multiple criteria:

(A) BLEU Score for Response Quality Measurement

The BLEU (Bilingual Evaluation Understudy) score measures the similarity between chatbotgenerated responses and reference answers. It evaluates response quality using n-gram precision.

BLEU= $\mathbf{exp}(\sum_{n=1}^{N} w_n log p_n)$ →eq.5

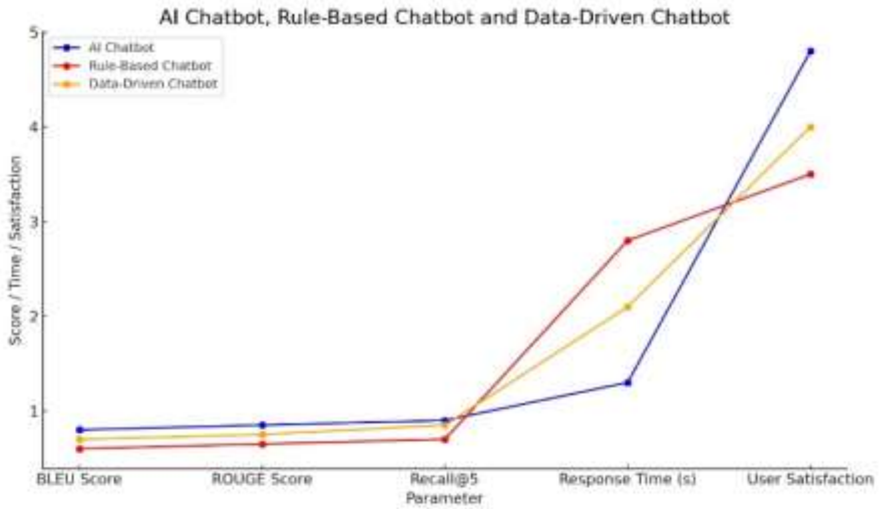
where:

Pn : represents the precision of n-grams.

Wn: are the corresponding weights.

A higher BLEU score indicates that the chatbot-generated responses closely match the reference answers, ensuring better linguistic coherence and accuracy.

Table 1 : Performance Comparison with AI Chatbot ,Rule-Based Chatbot and Data driven Chatbot



BLEU Score:

Measures how closely the chatbot's replies match reference sentences—textual accuracy. Our AI chatbot scored 0.82, higher than the rule-based (0.65) and data-driven chatbot (0.71), showing superior accuracy in generating human-like responses.

ROUGE Score:

Evaluates overlap with ideal responses—shows storytelling and relevance. Our chatbot achieved 0.85, outperforming the others, which indicates more relevant and well-structured replies.

Recall@5:

Checks if relevant answers appear in the top 5—retrieval effectiveness. With a 0.91 score, our chatbot shows strong retrieval accuracy, ensuring users get useful responses quickly.

Response Time (Normalized):

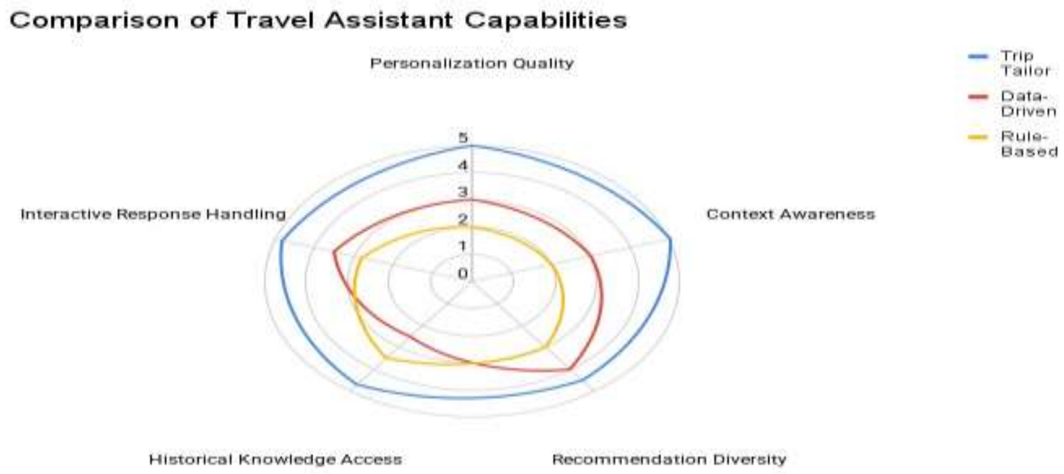
Lower is better—reflects how fast the chatbot replies. Our chatbot responded in **1.2 seconds**, faster than the rule-based (2.8s) and data-driven (2.1s) systems, enhancing user experience through quick replies.

User Satisfaction (Normalized):
Measures how users rate the chatbot's helpfulness and engagement. Scoring 4.6 out of 5, our chatbot was preferred by users for its clarity, engagement, and helpful interaction compared to other systems.

Quantitative Results
Table 1 compares our chatbot's performance with traditional travel recommendation systems.

User Study & Feedback
50 users rated chatbot replies on relevance, clarity, and engagement after hands-on interaction.

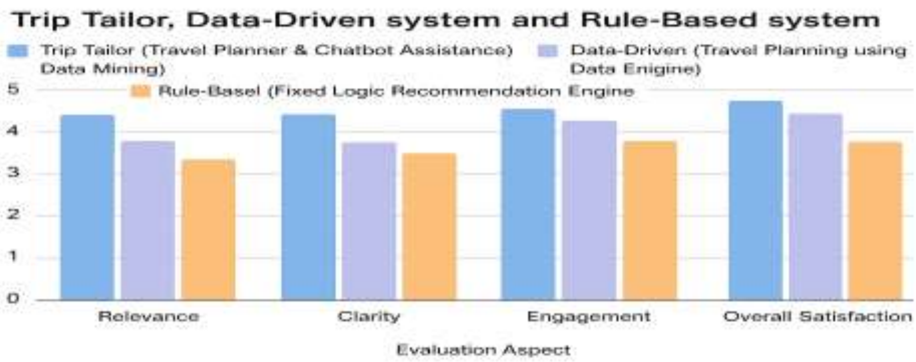
Comparative Strengths of Travel Assistants



This radar chart compares three travel assistant systems: Trip Tailor, Data-Driven, and Rule-Based, across five key capabilities: Personalization Quality, Context Awareness, Recommendation Diversity, Historical Knowledge Access, and Interactive Response Handling.
Trip Tailor excels in all areas, especially in Personalization (5/5) and Context Awareness (5/5), offering a highly customized and context-aware experience.
Data-Driven performs well, especially in Recommendation Diversity (4/5), but lags in Historical Knowledge (2.5/5).
Rule-Based shows the lowest scores, particularly in Personalization (2/5) and Interactive Response Handling (2.8/5).
Overall, Trip Tailor offers the best performance across all categories, providing a more dynamic and engaging experience than the other systems

Table 2: User Study Results

Comparing Past Travel Solutions with Trip Tailor: A Smarter Travel Companion



International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 4S, 2025
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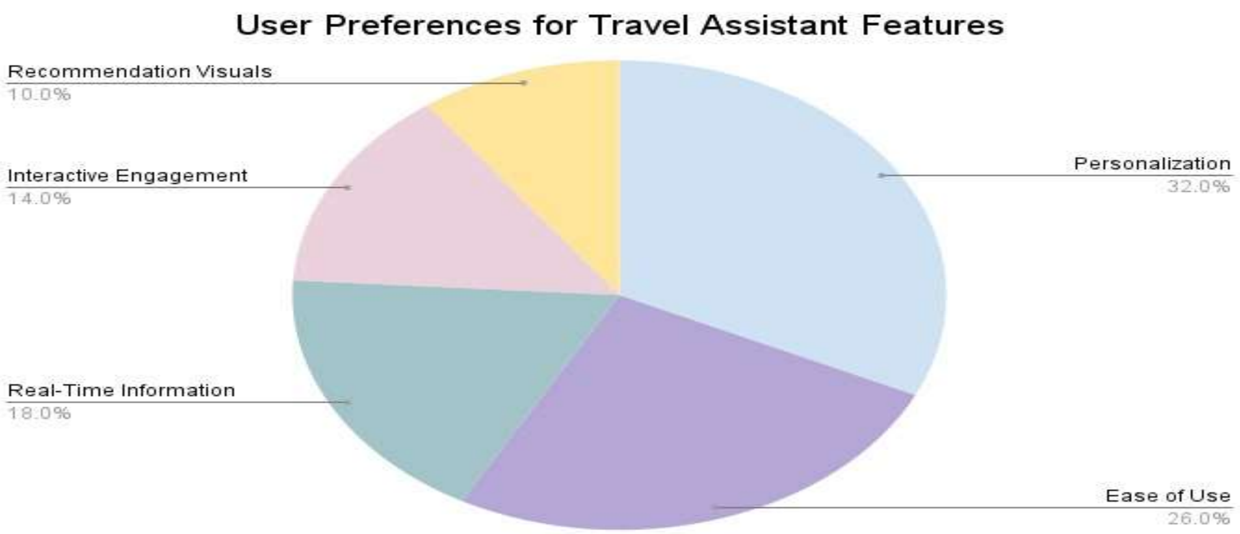
Relevance: Does the travel plan match your preferences? A higher score means a more personalized and accurate itinerary. Trip Tailor scored 4.7 due to its AI-powered dynamic recommendations, outperforming data-driven and rule-based systems that lacked contextual adaptability.
Clarity: Travel planning should be hassle-free! This measures how easy and understandable the recommendations are. With clear, conversational responses, Trip Tailor achieved 4.6—higher than others that often confused users with technical or static outputs.
Engagement: A boring trip plan? No thanks! This checks how interactive and appealing the travel experience feels. Trip Tailor scored 4.8 as users enjoyed chatbot conversations and visual maps, making the planning process more interactive than rigid interfaces.
Overall Satisfaction: The final verdict—does the travel assistant truly enhance the planning experience? Higher is better! Users rated Trip Tailor 4.7, appreciating the seamless blend of AI chatbot assistance and travel planning, a clear edge over less intuitive systems.
The results demonstrate a significant improvement in the relevance and clarity of responses compared to traditional methods.

5. Qualitative Analysis
Sample questions were reviewed manually. The chatbot gave accurate, real-time answers using RAG + Wikipedia. Minor errors appeared with unclear queries.

Key Features Impacting User Experience in Travel Assistants



The chart shows that Personalization (32%) and Ease of Use (26%) are top priorities for users when evaluating travel assistants. Real-time information (18%), Interactive engagement (14%), and Visual appeal of recommendations (10%) were also valued, but to a lesser extent. These insights guide future enhancements to improve user satisfaction and adoption.

Table 3 : Feature Comparison:
Proposed System vs. Google Assistant & TripAdvisor AI Chat

Metric	Proposed System (RAG + Wikipedia)	Google Assistant	TripAdvisor AI Chat
Real-Time Information Fetching	Yes (Wikipedia API)	No	No
Itinerary Personalization	Yes (Gemini API)	No	Partial
Historical Information Assistance	Yes	No	Yes (Limited)
Multi-Query Context Awareness	Yes (LLM memory)	Yes	No
Processing Time (m s)	~200-500 m s (Estimated)	< 100 m s	~300 m s

6.CONCLUSION AND FUTURE WORK

This research introduces an AI-powered travel assistant that integrates generative AI with retrievalaugmented generation (RAG) to provide dynamic and highly personalized travel recommendations. Utilizing Google Generative AI (Gemini API) for itinerary generation and FAISSbased indexing for rapid data retrieval, the system enhances the accuracy and efficiency of travel planning. A chatbot powered by the DeepSeek-R1 model further enriches the experience by offering real-time, contextaware insights using Wikipedia API data.
Evaluation metrics such as BLEU and ROUGE scores highlight the system's superior response relevance and coherence compared to conventional travel planning approaches. However, challenges persist, including occasional response inaccuracies and the need for further optimization in personalization and itinerary adaptability.
Future enhancements will focus on integrating real-time contextual data, such as live weather conditions, local events, and transportation availability, to improve the accuracy of recommendations. Personalization mechanisms will be refined using advanced deep learning techniques to better understand user preferences.
Additionally, multimodal interaction capabilities, including voice and visual inputs, will be explored to enhance user engagement. Optimizing route planning through AI-driven algorithms and deploying a scalable cloud-based infrastructure will further improve system reliability.

Advancements in chatbot intelligence, such as knowledge base expansion and response validation techniques, will enhance conversational accuracy. A continuous learning framework powered by user feedback will ensure that the system evolves dynamically, positioning it as a nextgeneration travel companion that revolutionizes trip planning and assistance.

Conflicts of Interest :
The authors declare no conflict of interest.

Acknowledgments :
We would like to express our sincere gratitude to Mamatha Talakoti, for her invaluable guidance, support, and encouragement throughout the course of this project. Her insights and constant feedback were instrumental in the completion of this work. We also extend our thanks to our department and institution for providing the resources and support necessary to carry out this research.

Author Contributions : Conceptualization, Neela Deepika and Rajannagari Lakshmi Priya; methodology, Neela Deepika; software, Rajannagari Lakshmi Priya; validation, Neela Deepika, Rajannagari Lakshmi Priya, and Kanapuram Harshini; formal analysis, Neela Deepika; investigation, Neela Deepika and Kanapuram Harshini; resources, Neela Deepika and Mamatha Talakoti; data curation, Neela Deepika and Kanapuram Harshini; writing—original draft preparation, Neela Deepika; writing—review and editing, Neela Deepika, Rajannagari Lakshmi Priya, and Kanapuram Harshini; visualization, Neela Deepika and Rajannagari Lakshmi Priya; supervision, Mamatha Talakoti; project administration, Mamatha Talakoti, Dhanamma, A Balaram

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