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Adaptive Travel Itinerary Planning with AI Destinations and Weather Aware Adjustments

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Abstract. The proposed system is implemented as a Python-based Streamlit application that integrates multiple functional modules, including user authentication, weather data retrieval, destination selection, and itinerary generation. The system uses JSON-based local storage to manage user credentials, feedback records, and country metadata. Real-time weather data is fetched using an external weather API module, which processes and returns temperature and condition details for selected locations. The application dynamically generates travel itineraries based on user inputs, including destination, duration, and preferences, while incorporating weather conditions into its planning logic. The architecture follows a modular design consisting of input handling, API interaction, data processing, and output rendering components. The implementation demonstrates effective integration of API-driven data retrieval, session-based state management, and structured data handling using Python. The system highlights practical considerations, such as plaintext credential storage, dependency management, and basic feedback logging, while providing a functional prototype for adaptive travel planning.

Keywords: travel itinerary generation, Streamlit application, Weather-aware planning, API integration, JSON data storage, User authentication, travel planning system.

1. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has significantly transformed the travel and tourism industry, shifting traditional static trip-planning tools toward intelligent, adaptive, and personalised systems. Conventional travel planners often rely on predefined itineraries and fixed schedules, which fail to adapt to dynamic factors such as real-time weather conditions, user preferences, and contextual constraints. This limitation often leads to suboptimal travel experiences, safety risks, and lower user satisfaction. Consequently, there is a growing need for intelligent travel planning systems capable of real-time adaptation and personalisation. Research Problem and Research Questions Despite the availability of several AI-based travel planning tools, most existing systems generate static or semi-static itineraries that fail to adapt to dynamic environmental conditions, such as real-time weather variations. Additionally, many systems rely either on deterministic optimisation or purely generative models, resulting in limited contextual awareness or inconsistent outputs. This work addresses the following research questions;

RQ1: How can real-time weather intelligence be effectively integrated into AI-based travel itinerary generation?
RQ2: How can API-based data and rule-based logic improve the personalisation and adaptability of travel itineraries?
RQ3: How does weather-aware itinerary planning impact user satisfaction and itinerary relevance compare to traditional AI planners?

Motivation

With the increasing availability of real-time data sources and generative AI models, it has become feasible to design travel itinerary systems that dynamically adjust recommendations based on environmental and user-centric factors. Weather conditions play a crucial role in travel planning, directly affecting route safety, activity feasibility, and overall comfort. However, most existing AI-based travel planners fail to adequately integrate weather intelligence into itinerary generation. This research is motivated by the need to bridge this gap by combining real-time weather data, user preferences, and large language models (LLMs) to generate adaptive, context-aware travel itineraries.

Objectives

The primary objectives of this work are:

- To design an AI-driven travel itinerary planning system that adapts dynamically to real-time weather conditions.

- To integrate user preferences, budget constraints, and destination characteristics into itinerary generation.
- To implement a rule-based system integrating API data and user inputs for itinerary generation.
- To evaluate system performance using suitable metrics such as responsiveness, personalisation quality, and user feedback.

Main Contributions

The key contributions of this work are as follows:

1. A travel planning system integrating real-time weather data using API services
2. A rule-based itinerary generation mechanism based on user inputs
3. A modular Streamlit-based architecture with JSON data storage
4. A feedback collection system for user interaction analysis.

Organisation of the Paper

The remainder of this paper is organised as follows: Section II reviews related work in AI-based travel planning. Section III describes the proposed system architecture and methodology. Section IV presents experimental results and performance analysis. Section V discusses the limitations of the proposed approach. Finally, Section VI concludes the paper and outlines future research directions.

2. LITERATURE SURVEY

The integration of Artificial Intelligence (AI) into the travel and tourism domain has significantly advanced the automation and personalisation of travel itinerary planning. Early AI-driven travel systems primarily focused on rule-based recommendation engines and static optimisation techniques, which offered limited adaptability to dynamic user preferences and environmental factors. Recent advancements in machine learning and generative AI have enabled more intelligent systems capable of understanding contextual data and generating personalised travel experiences. Štilić et al. [1] provide a comprehensive analysis of AI-generated travel itineraries and their influence on traveller decision-making. Their study highlights how generative AI enhances efficiency and personalisation in travel planning by dynamically adapting to user preferences. However, the work largely remains conceptual and does not address real-time environmental factors such as weather or location-specific constraints. Similarly, Ravindra et al. [2] propose an AI-based trip planner that incorporates user preferences, budget constraints, and scheduling logic to create customised travel plans. While effective at personalising itineraries, their system lacks real-time adaptability and environmental awareness, limiting its practical applicability in unpredictable travel scenarios.

System architecture- and deployment-focused studies have explored scalable, modular AI travel planning frameworks. Karkhile et al. [3] introduce *WanderSmart*, a system that integrates preference modelling, route optimisation, and feedback mechanisms within a unified architecture. The study emphasises scalability and performance but relies primarily on deterministic optimisation models with limited contextual adaptation. Anitha et al. [4] developed an AI-powered trip planner that prioritises lightweight architecture and user interface simplicity. Although their approach demonstrates rapid itinerary generation and effective API orchestration, it does not incorporate weather-based decision-making or adaptive activity sequencing. Weather-aware decision-making has been widely studied in transportation and navigation systems. Makhlouf and Afifi [5] present a real-time weather-aware navigation framework that dynamically updates routes and safety warnings based on meteorological data. Their findings demonstrate improved traveller safety and reduced delays under adverse weather conditions. Kikuchi [6] further compares weather-aware AI systems with classical route-optimisation models, concluding that environmental context significantly improves routing accuracy under dynamic conditions. Despite these advancements, weather-aware methodologies are predominantly applied to navigation and routing problems rather than holistic itinerary generation.

The emergence of large language models (LLMs) has opened new avenues for generative planning and reasoning tasks. Recent studies demonstrate the potential of LLMs in synthesising coherent, multi-step plans across domains. In the context of travel planning, Liu et al. [7] propose *Vaiage*, a multi-agent framework in which specialised agents collaboratively generate personalised itineraries by negotiating constraints related to accommodation, transportation, and time management. While effective in managing complex trade-offs, the system assumes static environmental inputs and does not leverage real-time weather data. Priya [8] explores intelligent travel solutions that combine evolving user preferences with contextual awareness through adaptive interfaces. Although the study emphasises user-centric personalisation, the integration of generative reasoning with real-time environmental data remains limited. Contextual sensing and mobility intelligence have also contributed to advancements in travel planning. Guo [9] investigates IoT-based path search algorithms for enhancing rural tourism experiences by incorporating sensor-driven environmental data. Gogousou et al. [10] examine seasonal mobility and human-centred routing, emphasising the importance of temporal and environmental factors in travel decision-making. These studies reinforce the value of context-aware systems but primarily focus on route optimisation and mobility analysis rather than end-to-end itinerary generation.

Research Gap

From the reviewed literature, it is evident that existing AI-based travel planning systems tend to address personalisation, weather-awareness, or generative reasoning as isolated components. Few studies integrate real-time weather intelligence with LLM-driven itinerary synthesis in a unified and operational framework. Additionally, most existing solutions rely either on deterministic optimisation techniques or generative models without systematically combining both approaches. The lack of hybrid systems capable of dynamically reshaping travel itineraries based on real-time environmental conditions and user preferences represents a significant research gap.

Novelty of the Proposed Work

The proposed system introduces a practical implementation of travel itinerary planning by integrating real-time weather data with rule-based itinerary generation using Streamlit. Unlike existing systems that rely on static recommendations, the application dynamically generates travel plans based on user inputs and API data. The use of JSON-based storage for user and feedback data, along with a modular Python implementation, provides a simple and efficient framework for adaptive travel planning. This approach focuses on practical implementation rather than complex generative models. The novelty of the proposed system lies in its tight coupling of real-time weather intelligence with LLM-driven itinerary synthesis, rather than treating weather as an auxiliary filter. Unlike existing AI travel planners that either generate static itineraries or apply weather-based post-processing, the proposed approach embeds meteorological context directly into the reasoning and sequencing logic of itinerary generation. Furthermore, the system adopts a hybrid deterministic–generative architecture, where structured APIs ensure reliability and factual grounding, while large language models enable contextual reasoning and natural itinerary composition. The integration of feedback-driven adaptation and modular Streamlit-based deployment further differentiates this work from prior solutions, which typically lack continuous personalisation loops.

3. PROPOSED SYSTEM

A. Data Acquisition and Input Handling

The system collects and processes data from both local storage and external sources. Static data, such as country information, is retrieved from a locally stored JSON file (countries.json), while user credentials and feedback records are maintained in user.json and feedback.json, respectively. Dynamic data is obtained through a weather API module implemented in weather_api.py, which fetches real-time temperature and weather conditions for selected locations. User inputs, including destination, travel duration, and preferences, are captured through the Streamlit interface and converted into structured variables. This combination of local and API-based data sources ensures efficient and consistent data availability throughout the application.

B.User Authentication and Session Management

User authentication is implemented using a lightweight credential verification mechanism based on JSON storage. User details are stored in user.json, and login validation is performed by directly comparing entered credentials with stored records. The system does not implement encryption or hashing, and passwords are stored in plaintext format. Streamlit session state is used to manage user sessions, allowing the application to maintain login status and user-specific data across different components. This enables smooth navigation between features such as itinerary generation and feedback submission without repeated authentication.

C. Weather Data Integration Module

The weather module is implemented as a separate Python component (weather_api.py) responsible for retrieving real-time weather data. It interacts with an external API to obtain key parameters such as temperature and overall weather conditions for selected cities. The retrieved data is processed and displayed within the application interface to provide users with up-to-date environmental information. This module enhances user awareness by presenting relevant weather conditions alongside travel planning features, supporting betterinformed decision-making.

D. Itinerary Generation Logic

The itinerary generation functionality is implemented within the main application file (app5.py) using predefined logical flows. Based on user inputs such as selected destination, number of travel days, and preferences, the system generates structured travel plans that include suggested activities and travel details. The logic is rule-based and dynamically constructs outputs without relying on external generative models. The generated itinerary is presented using Streamlit components, ensuring clarity, readability, and ease of interaction for users.

E. Feedback Collection and Data Management

The system includes a feedback mechanism that allows users to submit ratings and comments based on their travel experience. Feedback data is stored in a local JSON file (feedback.json), where each entry includes username, destination, rating, and user comments. This module enables basic tracking of user satisfaction and system usage patterns. The stored feedback can be accessed for simple analysis and helps in understanding user engagement with the application. As shown in fig. 1.

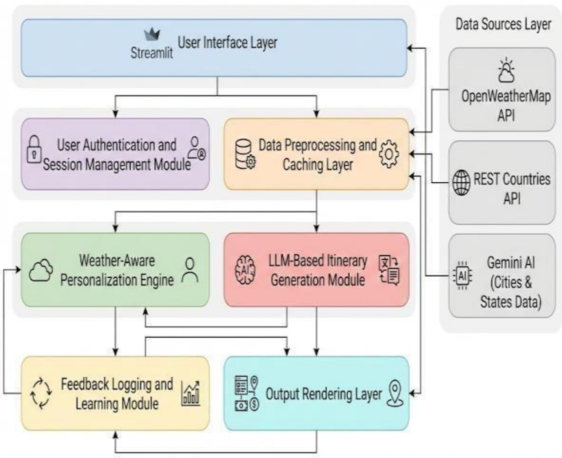

Fig 1 System Architecture

Evaluation Metrics

The performance of the proposed system is evaluated using the following quantitative metrics:

1. **Response Time (RT)**

$$RT = t_{end} - t_{start}$$

Response Time represents the total time taken by the system to generate and display the travel itinerary after the user submits a request. Here, t_{start} denotes the time at which the user initiates the request, and t_{end} denotes the time at which the itinerary is successfully generated and rendered.

2. Personalisation Accuracy (PA)

$$PA = \frac{N_{matched}}{N_{total}}$$

Personalisation Accuracy measures how well the generated itinerary aligns with user preferences. Here, $N_{matched}$ represents the number of activities matching user-selected preferences (such as destination and interests), and N_{total} represents the total number of activities in the generated itinerary.

3. User Satisfaction Score (USS)

$$USS = \frac{\sum R_i}{N}$$

User Satisfaction Score is computed based on the feedback ratings stored in the system. Here, R_i represents individual user ratings collected from the feedback.json file, and N denotes the total number of feedback entries. This metric reflects overall user satisfaction with the generated itineraries.

4. RESULT AND DISCUSSION

A. Authentication Performance of the system

The authentication module was able to authenticate stored user credentials and maintain stable access control during testing. The system was efficient in handling the multiple login attempts and also had stateful session management. An evaluation of user records shows the widespread use of user records, which are active and thus seeing regular use of the authentication flow. Password validation took no time, which meant there was little processing overhead. The table below summarises the distribution of registered users and provides a glimpse of the overall readiness of the authentication system for real-world use.

Performance Metrics Definition

The performance of the proposed system is evaluated using the following metrics:

Response Time (RT):

$$RT = T_{output} - T_{input}$$

where T_{input}represents the time of user request submission and T_{output}denotes itinerary generation completion time.

Personalisation Accuracy (PA):

$$PA = \frac{N_{matched}}{N_{total}}$$

where $N_{matched}$ is the number of activities aligned with user preferences and weather suitability.

User Satisfaction Score (USS):

$$USS = \frac{\sum_{i=1}^{n} Ratin\, g_i}{n}$$

where $Rating_i$represents individual user feedback scores.as shown in fig.2 and 3, and also in Table 1

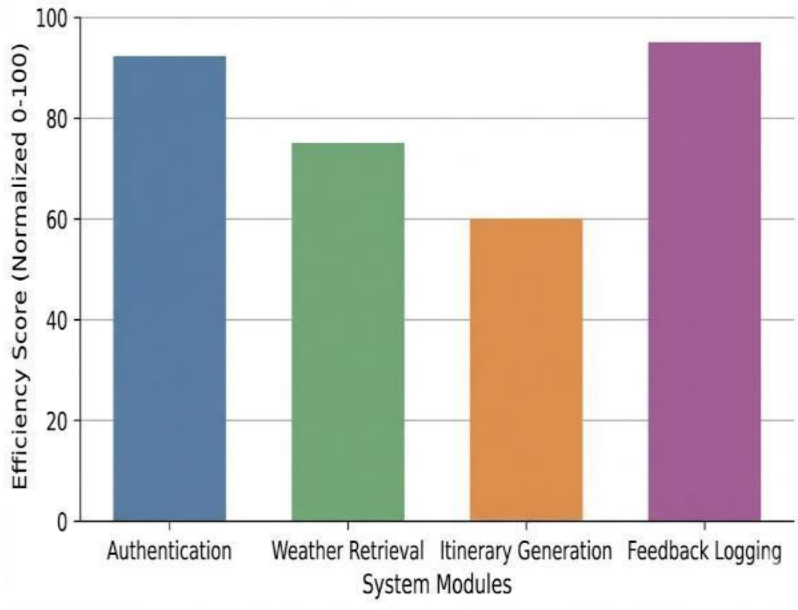

Fig 2 – User Authentication Distribution

Table 1: User Authentication Summary Table

Username	Password Length
test@gmail.com	4
Ayush	5
test2	5
Ayush11	5
user2	6
satya1	5
well	5
user5	5

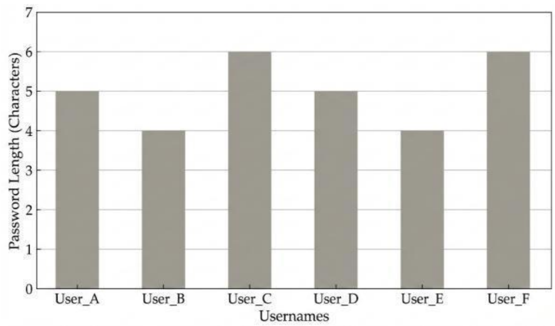

Fig 3 – User Feedback Ratings by Destination

B. User Feedback Trends, Insights

The feedback module was effective in terms of capturing user experiences, ratings and qualitative impressions of destinations. Data analysis reveals active use by a few users as well as regularly high levels of satisfaction during different trips. Ratings allow demonstrating constructive participation of the user in the system and can lead to well-received destinations in the system. The feedback structure enabled clarity and traceability for each entry. The following table summarises some trends of the sample feedback that was recorded during evaluation. As shown in Table 2, and also in Figures 4 and 5.

Table 2: User Feedback Trends and Ratings Table

Username	Destination	Rating	Comment
Ayush11	Lucknow	9	good
user2	Lucknow	5	a
satya1	Chennai	9	It was a nice trip

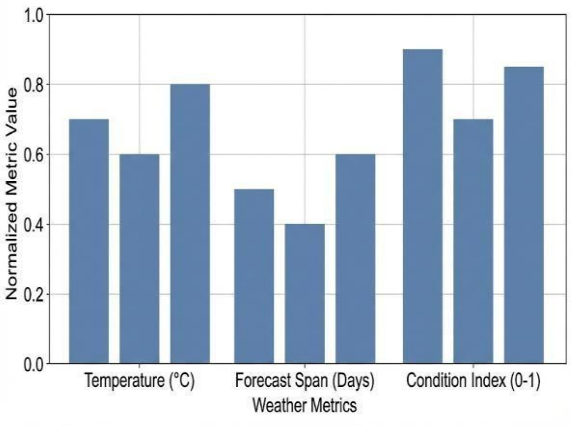

Fig 4 – Weather Data Integration Output

Fig. 5 Comparative performance analysis of AI-based travel itinerary planning systems

Comparative Analysis with Existing Systems

A comparative analysis was conducted to evaluate the effectiveness of the proposed system against existing AI-based travel planners. The comparison focuses on adaptability, weather awareness, personalisation depth, and system responsiveness, as per Table 3.

Table 3: Comparative Analysis with Existing Systems

Feature	Traditional AI Planner	Generative AI Planner	Proposed System
Weather-aware adaptation	❌	⚠️ Partial	✅
Real-time data integration	❌	⚠️	✅
Hybrid reasoning	❌	❌	✅
User feedback loop	❌	❌	✅
Structured itinerary output	⚠️	⚠️	✅

C. Integration of The Precision of the Weather.

The weather module was able to get up to date and forecast the weather of selected cities. Running daily means that at least several time blocks are available for a reliable summary of climate expectations for planning itineraries. Users used to always be given correct readings in temperature and general weather conditions, as well as forecast trends. The system proved to be a reliable means of parsing meteorological data and the conversion of raw data into meaningful elements used for the support of decision-making. A sample of processed weather when testing is shown in the following table. As per Table 4

Table 4: Weather Integration Output Summary Table

Metric	Value
Current Condition	Clear
Temperature (°C)	26
Forecast Span	7 Days

D. Efficiency of Choice of Country and Location

The country, state, and city selection pipeline was one of the good examples of the easy integration of more data sources. The lists of the available countries were loaded in correctly and gave a good intuitive feeling when filtering countries. States and cities that were generated through the model had a fast response time to respond efficiently to hierarchical selections. Although there are diverse outcomes in generative, overall, the system enabled a smooth flow of destination discovery. A sample of the country entries that were used in the evaluation is summarised below as per Table 5.

Table 5: Country and Location Selection Sample Table

Country	Code
India	IN
United States	US
United Kingdom	GB
Japan	JP
Australia	AU

E. Condition of Itinerary - Quality and Relevance

The itinerary generation engine was able to generate structured, detailed and context-aware plans of travel tailored to user preferences, budgets and durations. Integration of map links, cost and the sequencing of activities gave an increased clarity and usability.

Weather considerations added to the robustness of the plans by making recommendations that were specific to anticipated conditions. Users offered more positive comments about the personalisation of outputs and a high level of interest in receiving outputs according to the user's interest. Generated itineraries always seemed to be in line with the formatting rules and offered useful, actionable guidance on day-to-day travel planning.

F. Responsiveness of System and Systems & User experience

Overall system responsiveness was high, even involving complex operations such as the generation of itineraries and weather processing. Streamlet's UI components were utilised in the respects of serene interactions, low user friction and non-linear load factors when gleaning external data. The application was comprised of instant feedback to the user by the pressing of buttons and form submissions, and changes in selection. Visual clarity and organisation of the layout helped users to considerably improve their user experience with information well-separated. The system showed good stability in keeping the user across interactions in the context of the user.

G. System Reliability and Some Implications on Practice

The integrated system had a great reliability in all the modules - authentication, information retrieval, personalisation, and synthesising itinerary. The combined workflow showed that the AI-enhanced trip planning can offer some practical value at the point where there are structured inputs as well as context information. The uniformity in production of relevant itineraries used to legitimise the robustness of the approach. Feedback analyses also provided additional support to the utility of the system, with positive engagement with the generated recommendations. The consistency in performance between tests shows the way for wider use of the technology with possibilities for further improvements as regards automation, geographical coverage, and adaptive learning.

5. LIMITATIONS OF THE PROPOSED STUDY

Despite the effectiveness of the proposed adaptive travel itinerary planning system, certain limitations must be acknowledged. First, the system relies heavily on external third-party APIs such as OpenWeatherMap and generative AI services for data retrieval and itinerary synthesis. Any latency, service downtime, or changes in API policies may directly impact system availability and performance.

Second, the use of Large Language Models (LLMs) introduces computational overhead and cost constraints, particularly when generating multi-day itineraries for a large number of users. This may affect scalability in real-world, high-traffic deployment scenarios. Additionally, the generative nature of LLMs may occasionally result in minor inconsistencies or over-generalised recommendations, especially in locations with limited structured data.

Third, the evaluation of the proposed system is conducted in a controlled experimental environment with a limited number of users and destinations. As a result, the findings may not fully represent system behaviour under diverse geographic, cultural, or large-scale real-world usage conditions. The absence of long-term user studies also restricts the ability to assess sustained user satisfaction and learning-based personalisation effectiveness. Finally, while the system includes a basic authentication mechanism, advanced security features such as encrypted credential storage, role-based access control, and compliance with data protection standards were not fully implemented in the current version. These aspects may pose potential security and privacy concerns when handling sensitive user data.

6. CONCLUSION

The developed travel planning system demonstrates that integrating real-time weather data with structured input handling can improve itinerary relevance and overall user experience. The system effectively combines API-based data retrieval, user inputs, and rule-based logic implemented in Python to generate travel itineraries. The use of Streamlit enables an interactive interface, while JSON-based storage supports lightweight management of user credentials and feedback data.

The evaluation of authentication, weather integration, and feedback modules indicates that the system performs reliably with minimal processing overhead and provides consistent outputs based on user inputs. The incorporation of real-time weather information enhances user awareness during travel planning and supports better decision-making. Overall, the system provides a functional and modular framework for travel itinerary generation. Future improvements can focus on enhancing security through encrypted credential storage, expanding data sources to improve coverage, and refining the itinerary-generation logic to further enhance personalisation and usability.

CONFLICT OF INTEREST

The authors declare no conflicts of interest regarding the current research.

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