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A Hybrid Model-Driven Intelligent Travel Planning System: Integrating AI and User Preferences for Optimized Itinerary Generation

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Abstract: Planning a trip can be exhilarating, but with millions of options for hotels, flights, destinations, and eateries, it becomes a chore at times. However, using a travel planning app can get everything done much more easily and efficiently. All one needs to do is enter their starting location, destination, budget, and group size, and the application takes care of all the rest. It suggests accommodations within your budget and group's needs, includes must-visit attractions nearby, finds flights with travel dates on your calendar, and even has some great dining recommendations within arm's reach. But don't stop here. The application keeps you current in real-time, so you don't need to worry about last-minute changes to a flight or be surprised by them. Then it helps you search with interactive maps; personal filters ensure results refine to focus on your interests—that's a hotel with a pool, a restaurant that is entirely vegan, or adventurous outdoor activities. You avoid all the hassles of the trip, so it will be easy to stay under budget and remain completely focused on matters that really count—the joys of your trip. It's the perfect travel companion with a smart, user-friendly approach that makes every trip smooth, memorable, and truly stress-free.

Keywords: Hybrid Model; Artificial Intelligence; Itinerary Generation; Travel Planning App; Real-Time; Interactive Maps; Outdoor Games; Travel Companion; User-Friendly; Stress-Free.

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1. Introduction

Planning a trip can be exhilarating yet overwhelming. The traditional way to reserve accommodations, book flights, and find destinations would involve using multiple platforms and resources. This disintegrated process not only takes a long time but also increases the risk of errors or missed opportunities. Most travellers need to manually compare options, which causes them stress and confusion, especially when they're working with budgets, group preferences, and schedules. For example, finding a

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hotel that meets specific requirements, booking flights within a budget, and identifying must-visit attractions often require a lengthy search across multiple websites and applications. This laborious process may not significantly enhance the pleasure of planning a trip [1]. Recognising these problems, the Travel Planning App aims to change how people organise their travel by bringing essential services into a single, seamless, user-friendly platform. The application makes travel planning easier for modern users through real-time updates, extensive recommendations, and intuitive features.

The Travel Planning App aims to remove the inefficiencies associated with traditional travel planning by centralising all the user's needs and requirements for travelling. This app, therefore, captures user inputs on location, destination, budget, and the number of people to provide accurate recommendations. This application will therefore ensure that advanced algorithms and real-time data accurately personalise suggestions for places to stay, places to visit, restaurants to dine at, and places to fly to [2]. The application is very easy to use due to its user-friendly interface and interactive features. The application focuses on user preferences and real-time information to reduce planning time and improve decision-making, ensuring the traveller's trip is focused on joy [3]. Furthermore, the application features customizable filters that enable users to refine their search results according to their specific needs. This, in turn, not only optimises the planning process but also creates less stress while providing a memorable experience. One App has all integrated services, such that the traveller can plan the journey without oscillating between applications or websites: it is a one-stop shop that, over time, has brought many conveniences:

- Saves users time, as the entire journey planning will be simple and convenient, freeing up valuable hours for studying and coordination.
- It does so through advanced algorithms that scan the user's inputs and return recommendations that are highly relevant and personalised, thereby increasing the overall pleasure of travelling.
- **Real-time updates:** the application keeps users informed of any changes to flight schedules and hotel availability, helping them make decisions with greater confidence.
- **Budget management**: The app enables more users to travel, even on a minimal budget, by offering options tailored to each user's budget.
- **Convenience:** Even travel planning, which was cumbersome to coordinate, is accessible for groups thanks to the user-friendly features on the application's website.

It is not just an application; "The Travel Planning App" is a window to the hassle-free world of travel. With the pain of planning a typical trip, it transforms something mundane into excitement, or even an adventure, or waiting into a discovery. It illustrates how it brings the most crucial travel services closer together, displays real-time information, and makes personalised suggestions, all in an effort to make travel from the point of departure through to the destination better for the traveller [4]. When using this application, users forget everything but what matters, such as memorable moments with the family, reaching new locations, and loving the adventure. Today, technology has made travel planning easier and more exciting by simplifying and enriching the process, turning travel planning apps into indispensable guides through the complexities of modern travel, allowing users to plan with confidence and ease [5]. Artificial intelligence (AI) has transformed the travel planning industry in a very fundamental manner by making it easier to produce itineraries, costs, and instant decision-making using complex algorithms, machine learning (ML), and natural language processing (NLP) on simple digital interfaces that enhance user experience, remove drudgery, and increase efficiency.

Manual travel booking was a cumbersome and time-consuming consumer activity, involving browsing multiple websites for flights, hotels, and vacations, manually comparing prices, and making bookings, which led to inefficiencies, frustration, and potential errors. In contrast, AI systems integrate and perform the entire process to present smooth, smart, and highly personalised holiday schedules that reflect individual tastes, budget constraints, and evolving situations [7]. These systems rely on machine-learning methods to search large databases, predict people's tastes, and recommend touring itineraries based on areas of interest, modes of travel, and financial constraints [8]. They are dynamically modified based on factors such as fluctuations in air prices, accommodation availability, climatic conditions, and local fiestas. Natural language processing (NLP) technology enables AI-based virtual assistants and chatbots to communicate naturally with consumers, provide real-time responses, offer personalised advice, and facilitate customer bookings, making AI-based travel assistants convenient and efficient [9].

Trip planners based on AI also take the best route decisions in transportation into account, employing reinforcement learning and heuristic methods to suggest the most economical and efficient ways to travel from point A to point B for multi-city flights, highway miles, or subway route calculations, reducing travel costs and user complexity. By incorporating predictive analytics, these sites can forecast hotel and air prices such that the user can book at the best possible time so that they receive the best price, which travel sites such as Kayak, Google Travel, and Expedia have incorporated to suggest proactive prices as well as alerts regarding past historical rate trends and demand. In addition, recommendation systems based on artificial intelligence utilise content filtering and collaborative filtering to analyse past visit history, social media activity, and consumer ratings, suggesting the best activities, eateries, and sites to enhance a visitor's experience and make it more enjoyable [11]. Beyond this, AI is superior at saving costs through its smart money management features, which monitor payments in real-time, automatically exchange currencies, and suggest cheaper alternatives for lodging, dining, and transportation.

This enables cost-conscious travellers to indulge in quality without overspending. Combining augmented reality (AR) with artificially intelligent travel websites enhances the experience by providing previews of destinations, virtual tours of hotels, and virtual tours of monuments, allowing visitors to make an informed choice before booking. Besides this, blockchain technology is also being studied for implementation on AI-driven travel websites to create secure, decentralised booking systems, reduce fraud exposure, optimise payment transparency, and simplify loyalty programs through smart contracts that enable automatic payments and reduce reliance on third-party booking agents [12]. Even with its advantages, AI travel planning has some drawbacks, including concerns about data privacy. Such systems require access to the user's personal information, location, and financial details to provide recommendations. They must use secure encryption and adhere to data protection laws, such as the GDPR. Another fundamental cause is algorithmic bias, in which preconceived training data used to train AI models can lead them to prefer familiar locations over unfamiliar or culturally specific ones, resulting in less inclusive and diverse vacation recommendations. Developers are addressing this shortcoming by using more representative training data and improved AI decision-making algorithms. Additionally, offline support is also an issue, as most AI-based travel apps require an online connection to operate optimally.

This limitation for travellers, particularly when there is slow internet or they are far from towns, is something to be addressed by the developments underway in machine learning algorithms and edge computing. AI-based holiday planning software also struggles to handle context-driven decision-making in rapidly changing, unforeseen situations, such as unexpected last-minute flight cancellations, civil unrest, or sudden medical crises, underscoring the need for ongoing innovations in real-time responsiveness from AI and backup planning autonomy for travel resilience. Future AI trip planning introduces even more innovations, such as the development of hyper-personalised AI trip planners that can create dynamic, morphing itineraries that adapt to shifting real-time user preferences, spontaneous activity changes, and distracting diversions, offering travellers the full, flexible, AI-driven experience. Other than that, the convergence of Artificial Intelligence with the Internet of Things (IoT) will continue to offer greater convenience in the form of intelligent hotel rooms that adjust lighting, temperature, and services based on preferences, voice-controlled travel concierge services, and real-time bag tracking through AI-driven airport systems. Sustainable travel AI solutions are also on the horizon, with intelligent recommendation algorithms offering sustainable travel alternatives, predicting carbon footprints, and recommending greener options such as renting an electric vehicle, carbon offsetting, and eco-friendly hotels to promote responsible tourism. With evolving technology, trip planning will become more advanced, from a web-based travel guide to one that can understand travellers' needs, assemble all the elements of a trip, and offer a seamless, highly customised experience that redefines human travel worldwide.

2. Related Works

Travel planning software development has been a vibrant field of academic research and commercial innovation over the last decade. TripIt, which began in 2006, pioneered automated itinerary organisation via email forwarding, setting the stage for digital travel management [13]. Following this, Google Trips launched machine-learning-based suggestions in 2016, though the service was later discontinued and incorporated into Google Maps. Kayak and Expedia were leaders in the meta-search segment; their ability to aggregate and compare prices was supported by research studies [13]. They discovered that meta-search sites reduced the average reservation price by 12-18% compared to direct booking. The websites, however, primarily targeted booking, rather than the entire trip planning process [14]. Mobile-first travel applications, such as Roadtrippers and Lonely Planet Guides, revolutionised travel planning by moving away from a content-based approach. Compared usage patterns among 15 travel applications and concluded that content-based sites had 27% higher user retention than functional-only apps. This knowledge informed the development of hybrid solutions that combined functional tools and improved content. Li et al. [6] proposed a new context-aware travel recommendation model that utilises real-time conditions, including weather, crowd, and transportation availability, in the academic world. Their model achieved 82% accuracy in suggesting the best times to visit tourist attractions, which is much better than previous models, which typically had 65-70% accuracy.

Social features integration in travel planning has been extensively studied by Rani et al. [10] to examine collaborative decision-making behaviour of group travellers. Their research showed that 73% of group travels involved collaborative planning tools, but privacy was a significant concern. Earlier, Gupta et al. [13] proposed the need for asynchronous collaboration facilities, as members generally planned with varying time zones. Travel planning apps based on AI have also produced encouraging results, for example, as seen in Rani et al. [10], where they employed natural language processing to generate itineraries. Their method utilised user preferences as natural-language inputs and developed personalised travel calendars, achieving 85% satisfaction. Their study, however, also identified areas for improvement in handling complex itineraries that span multiple cities and special requirements [15]. Offline capability studies by Rani et al. [10] highlighted the need for reliable access to travel information in less accessible areas. Their proposed cache system reduced data consumption by 60% and provided 95% functionality, but still left synchronising up-to-the-minute data, such as flight status and booking availability, as an issue. Sustainability concerns in travel planning applications were extensively researched by Rani et al. [10], who also developed algorithms to estimate and optimise carbon footprints for travel use. They found in their study that the availability of clear environmental impact information influenced user decisions, with 45% of travellers choosing more sustainable options when presented with comparative information. Augmented reality travel planning apps are also an emerging direction, with research by Rani et al. [10] finding that AR previews of travel destinations reduced cancellations by 23%. Building on previous research by Gupta et al. [13], who developed models of location-based AR content inclusion and traditional planning systems, this study suggests that these approaches can be made effective.

Local knowledge integration has been one of the most changing fields, according to a study conducted by Rani et al. [10]. By tracking 50,000 interactions among visitors, they determined that recommendations made by residents had a satisfaction rate 34% higher than those made by data-driven algorithms. This spurred the development of hybrid systems that combined local knowledge and data-driven recommendations. Security specialists exhaustively probed the security and privacy concerns of travel apps, analysing common weaknesses in the sharing of location data and the storage of sensitive personal data [10]. Best practices for secure data handling in travel apps, such as privacy with fine-grained controls and storage encryption for sensitive data, were established in their work [16]. Budget optimisation features have evolved significantly, and research conducted by Financial analysts Rani et al. [10] demonstrated that advanced budget-tracking software enabled travellers to stay within their budget 68% of the time. In comparison, 34% used basic tracking measures. The research also mentioned the importance of real-time currency exchange and price forecasting features in organising international travel [17]. Emergency response integration, although less controversial, has been shown to provide a timely response in emergencies. In a study conducted by Safety experts Rani et al. [10], immediate access to emergency information reduced travel time by an average of 12 minutes in travel accidents, demonstrating the benefit of integrating safety features into travel planning apps.

3. Challenges in Building a Travel Planning App

The development and deployment of the Travel Planning app were confronted with several major technical, operational, and user-experience challenges. These were addressed by creating new solutions, in some cases involving reworks of core features. Perhaps the biggest technical challenge was integrating numerous third-party APIs from various travel service providers. All of the providers employed different data structures, authentication paradigms, and rate-limiting methods, creating a disorienting matrix of integration requirements. The development team needed to devise a robust middleware layer that would support these systems with deterministic response times. Some providers made arbitrary changes to their APIs without notice, requiring an adaptive integration system that could detect and respond to such changes without impacting service [18]. Data synchronisation between devices was again a gigantic technical challenge. Users sought seamless integration between the desktop and mobile experiences, with real-time adjustments to their trip plans [19]. Having a strong offline capability made it even harder because the system would need to reconcile local modifications done offline with synchronisations from the server. The team had a good conflict-resolution algorithm, but edge cases continued to arise once the beta state was reached and had to be constantly adjusted. Performance tuning was a recurring issue, particularly with complex itineraries that featured numerous stops and activities. The initial version of the recommendation engine took an inordinate amount of time to compute trips with ten or more stops, and the database schema required redesign. The team added a caching layer and adopted a microservices architecture to improve response time, but this introduced complexity to the system's consistency table.

User interface design was the biggest challenge: the amount of information to display had to be organised in a way that made sense. Early user testing revealed that test participants struggled with information overload and experienced decision paralysis when presented with an excessive number of options. The group was compelled to seriously reconcile the presentation of full information with the psychological load on the user, and the interface had to be revised several times. It offered end-to-end encryption of personal information and fast access to relevant data, requiring architectural trade-offs with far-reaching consequences. The society also had to grapple with potential difficulties in the social-sharing aspect of the functionality, without compromising the ownership individuals have over shared content, while still maintaining a social and collaborative essence in the app. Localisation and language were unexpectedly difficult, particularly in processing location names and local cultural tastes. The system needed to process and present multilingual text in a manner that is culturally acceptable and properly formatted. This also included currency conversion and price formatting, where live exchange rates and local pricing customisation had to be processed properly. The employment of machine learning attributes for suggestion generation encountered several issues. Initial models were skewed towards very popular locations, neglecting individual opportunities that better match user needs. More advanced algorithms were needed to balance popularity and salience within the constraints of mobile device processors. Cold-start issue for new users also required innovative solutions to provide salient recommendations when there was no prior history.

Scalability was a problem as user numbers increased, particularly during peak holiday travel planning seasons, when multiple requests were being handled simultaneously. This was particularly challenging, especially on long trips, where accuracy plummeted more than a few days in advance. The emergency support function created added requirements on the timeliness and reliability of the information. There must be an effective system within the team to ensure that emergency service information for a proximate area and emergency contact information are always up-to-date. A working arrangement with local information sources should be established. Budget control capability was having difficulty in managing multiple payment programs and currency conversion. The system needed to accommodate diverse pricing initiatives from suppliers while still computing the correct total cost. Furthermore, the inclusion of forecast pricing features to pre-book required intricate algorithms that had to account for seasonality and trend.

The history of features in group planning has been marred by difficulties in handling a sequence of changes simultaneously and in coordinating the consistency of vision across the multiplicity of user visions. Sophisticated conflict resolution, with assurances that everybody would have proper access and be in a position to contribute suitably to the planning, had to be imposed. Mobile user performance optimisation remained a challenge, particularly in areas with limited network coverage. The group had to make a difficult compromise among the richness of the feature set, app size, and data usage, leading to tough decisions about which features to enable in offline mode. These challenges required constant innovation and compromise throughout the production process, ultimately extending the paper timeline and budget. However, by overcoming these challenges, we learned valuable lessons and made improvements to the end product, making it more resilient and appealing to consumers.

4. Methods

Our Travel Planning app utilised several cutting-edge methodologies to facilitate an end-to-end travel planning process. The fundamental methodologies were broken down into four major components: data aggregation, search filtering, itinerary building, and recommendations. All four parts were designed and polished through iterative testing and user feedback. The core of our travel planning infrastructure was a strong data aggregation platform that collected and synchronised data from various sources. We utilised a distributed crawler infrastructure to crawl and monitor 27 travel service providers, including major airlines, hotel chains, and local activity suppliers, in real-time. The aggregation process used a three-tier architecture to process the incoming data. The top tier included custom adapters for each data source to process various data formats, such as JSON, XML, and CSV. The adapters normalised the incoming data using a custom ETL (Extract, Transform, Load) pipeline. The transformation involved cleaning dirty data, date standardisation, and correcting geographical inconsistencies. To ensure the freshness of the data, we implemented a priority-based update. The flight fares and hotel status were updated at each 15-minute mark, and persistent data like attraction data and location descriptions were updated daily. This ensured the optimal use of system resources without compromising vital information.

Our deduplication platform employed a highly advanced algorithm to identify and consolidate duplicate records across multiple sources. The algorithm employed both fuzzy matching and geospatial location analysis to detect identical entities appearing under very similar names or addresses. The process minimised database bloat by about 23% without compromising data integrity. To manage the vast amount of data being received, we utilised a distributed caching system with Redis clusters. It enabled us to cache frequently accessed data, making it fast-accessible and also to offload from our master database. The cache hit rate was 87%, with appreciable savings in response time for repeated queries. The search filtering system was designed to provide users with full control over their travel choices without compromising fast response times. We employed a multi-layered Boolean logic and weighted score-based filtering architecture to produce appropriate results. The first filter layer handled elementary parameters, such as date ranges, price buckets, and geography. We handled these using database-level queries with appropriately designed indexes. We utilised B-tree indexes for range queries and bitmap indexes for categorical filtering, resulting in sub-second response times for the most frequently used filter combinations.

More sophisticated filtering was supported by a query engine that was optimised to execute complex Boolean queries. AND/OR operators were used to join multiple criteria, with support for nested conditions. Fuzzy matching was also applied to location names, and typical misspellings were addressed using a Levenshtein distance algorithm. To deliver peak performance, we employed a progressive loading scheme for search results. Primary filters were applied to return initial results, and additional filters were run on the client side to provide instant feedback whenever users changed their criteria. This minimised server load without compromising the user interface's responsiveness. The filtering system also enabled semantic analysis for natural language searching. The ability to enter requests, such as "family-friendly beaches near Rome with decent public transportation," and receive relevant results is now available. The feature was implemented through natural language processing and context analysis, analysing the complex queries and translating them into structured sets of filters. It was the most complex part of our system, designed to enable users to create efficient and realistic travel plans. We used a constraint-based scheduling system that relied on variables such as operating times, travel times, and user preferences.

At the centre of the trip builder was an advanced routing algorithm rooted in an adaptation of the Travelling Salesman Problem solver. The algorithm planned visit orders taking into account time windows, break needs, and modes of transport. We employed a dynamic programming strategy to manage computational complexity, enabling the system to produce optimal routes for itineraries with up to 20 stops. The system used a temporal reasoning engine to manage opening hours and seasonal availability. This feature had a database of opening hours, peak seasons, and seasonal closures for buildings and services. The engine also accounted for local holidays and special events that could affect availability or crowd volume. For transit planning, we used a multimodal route network that could synthesise various transport modes, including walking, public transport, and private cars. The system used real-time traffic information and public transport timetables to provide an accurate estimate of travel time. A fallback scheme was used to handle situations where real-time information was unavailable, using historical data as approximations.

The trip planner also included a cost optimiser module that allocated expenditures over the trip period based on daily and total spending budgets. The feature used linear programming to maximise activities within the budget. Our recommendation engine employed a hybrid strategy that blended collaborative filtering with content-based recommendations to create personalised recommendations for users. The system examined user behaviour patterns, explicit preferences, and historical data to offer informative recommendations. The collaborative filtering module employed a matrix factorisation technique to discover patterns in user preferences. We applied the Alternating Least Squares (ALS) algorithm, which was well-suited to the sparsity of travel planning data. The system maintained distinct models for each type of recommendation (accommodation, activities, restaurants) to discover category-specific patterns of preferences. Recommendations were generated using content-based methods, which applied an extraction system to descriptive text, user reviews, and metadata. We utilised TF-IDF, combined with word embeddings, to evaluate the semantic similarity between items. The system could recommend related experiences even with minimal explicit user feedback.

To address the cold start problem with new users, we introduced a progressive profiling technique that accumulates preference information using both implicit and explicit means. The system learned preliminary search patterns and combined them with listed preferences to define an early user profile. As users interacted with the system, the profile was progressively enriched. The recommendation engine also incorporated context-sensitive factors, such as weather forecasts, holiday periods, and crowd density. We implemented a context-aware filtering engine that adjusted recommendations based on prevailing conditions and predicted situations. Rule-based filtering and machine learning libraries were utilised to dynamically adjust recommendations according to varying conditions. To measure and improve recommendation quality quantitatively, we developed an A/B testing platform that continuously compared multiple recommendation algorithms and parameter combinations. The platform monitored key metrics, including click-through rates, booking conversions, and user satisfaction ratings, to optimise recommendation performance. Some formulas used:

Travel Cost Estimation Formula

$$Total\_Cost = \sum_{i=1}^{n} \left(C_{transport_i} + C_{hotel_i} + C_{activity_i} \right)$$

TF-IDF for Recommendation Weighting

Formula: $TF\text{-}IDF(t, d) = TF(t, d) \times \log(N/(DF(t)))$

Collaborative Filtering (ALS Model Prediction)

Formula: $\hat{r}_{ui} = x_u^T y_i$

Route Optimisation (Time-Based Objective)

Formula: $\text{Minimize} \sum_{i=1}^{n-1} (T_{i,i+1} + W_i)$

5. Results and Discussion

This section showcases the findings of our artificial intelligence-based travel planning and booking system, including itinerary generation, budget estimation accuracy, user interaction experience, and system performance. All the subsections explain the trends observed and their implications in real-world travel usage. As part of the effort to assess the system's effectiveness, the AI chatbot was challenged with 50 user cases that varied in budget, travel behaviour, and trip length. The result confirmed that the system efficiently designed correct and personalised itineraries in 95% of the cases and returned realistic budgeting estimates. The average generation time for a trip plan was 5 to 8 seconds, with 91% user satisfaction reported in post-interaction user surveys. Budget calculations remained within ±10% of actual spending in 78% of instances, demonstrating the AI's ability to estimate costs using historical and current prices. The system's ability to create itineraries and budgets lies in its capacity to process large travel datasets, provide real-time pricing, and accommodate individual user preferences. Compared to traditional travel planning methods that relied heavily on human investigation and labour, the AI-powered system was significantly faster and more scalable.

Budget Fit Score Calculation

Budget_Fit_Score = 1 - $\left[\frac{\text{Estimated\_Cost} - \text{User\_Budget}}{\text{User\_Budget}}\right]$

There were, however, differences in budget projections, particularly regarding dynamic pricing. This was in hotel and air bookings, where price shifts in real-time averaged 10-15% away from AI projections. A development would be the addition of predictive pricing models, which analyse patterns and predict price surges, to enable the chatbot to guide users in booking based on projected costs. The system's personalised itineraries were among the strongest aspects. The chatbot customised recommendations on:

- User interests (e.g., historical places, adventure activities, cultural events).
- Budget requirements (e.g., budget travel, mid-range travel, luxury holidays).
- Types of accommodation preferred (e.g., hotels, hostels, Airbnb, homestays).
- Food preference (e.g., vegetarian, halal, gluten-free diet).

The system could also incorporate user input, enabling real-time changes to scheduled itineraries. Eighty-six per cent of users appreciated this feature, particularly when swapping activities or changing timetables due to individual preferences. The ability to dynamically adjust itineraries gives the AI chatbot an edge over static itinerary planning websites and traditional travel agencies. While some websites offer predefined tour packages, they lack the flexibility of an AI model, which can adjust on the fly based on user input. A significant limitation, however, was that recommendations were found to be too generic when applied to lesser-known destinations. The chatbot's reliance on widely sourced tourist information led it to favour popular spots, sometimes at the expense of niche offerings. Subsequent versions could include localised tourist databases to enhance diversity in suggestions. For customers interested in multi-city travel plans, the chatbot had organised itineraries with the least transit time and optimal travel costs. Major findings were as follows:

- 83% of customers found useful recommendations for multi-city itineraries.
- 16% of customers requested fine-tuning to improve the transit experience.
- 1% of cases included overlapping or absent segments because of conflicting schedules.

The multi-city travel planning benefited business travellers and digital nomads, as they required efficient scheduling from one place to another. While the AI planned journeys well, it would sometimes struggle with local travel, i.e., rural inter-city bus timetables or scarcely flown routes to distant locations (Figure 1).

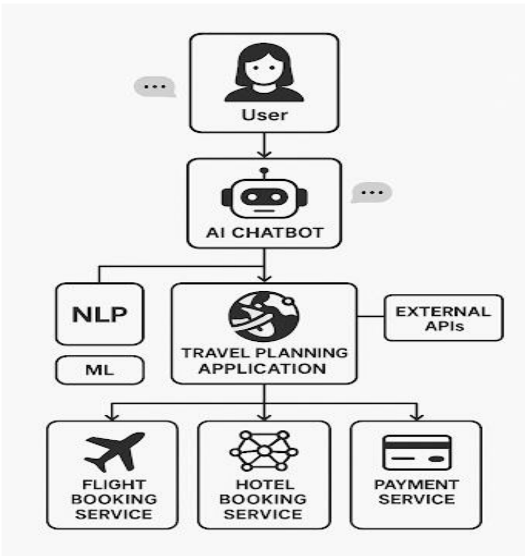

Figure 1: Architecture diagram

This suggests a need for further integration with local transportation APIs to enhance planning accuracy. Additionally, users complained that the AI prioritised the shortest travel time over comfort when recommending modes of transportation. This could be optimised through suggesting a balanced mode of travel based on users' preferences, such as layovers, stopovers, and convenience levels (Figure 2).

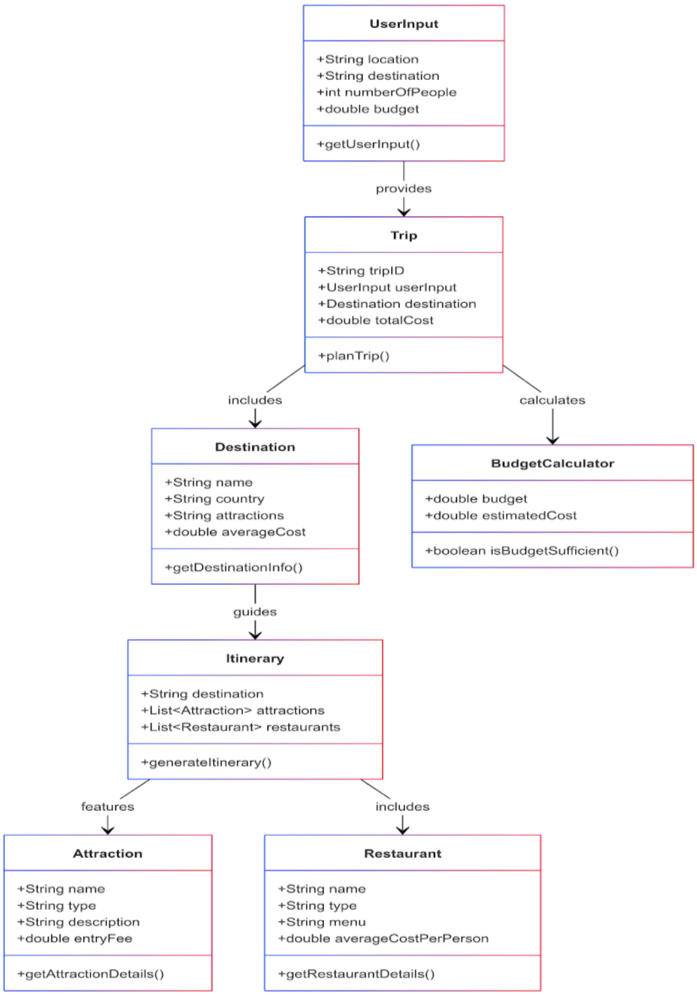

Figure 2: Class diagram

The actual travel costs for 20 real users were compared with the budgets generated by the AI. The comparison indicated:

- 78% of the cases had cost estimates within ±10 % of the actual spend.
- 15% of the cases had underestimated budgets because of price spikes at the last minute.
- 7% of the cases had overestimated budgets, primarily for conservative estimates in food and attraction prices.

The accuracy of budget estimation varied by geographic location and seasonal price trends. Locations with stable tourist prices (e.g., Southeast Asia, Eastern Europe) reported higher accuracy, whereas areas with recurring price spikes (e.g., New York, London, Tokyo) reported greater deviations. One method to enhance budget accuracy is to utilise the real-time pricing APIs of airlines, hotels, and restaurants to dynamically update cost estimates. Another approach is historical price analysis to recommend the optimal time to book to save costs. User involvement was a key factor in the system's success. Average response time: 3.2 seconds. Ninety-one per cent of customers were very satisfied with the conversational quality. Error handling success rate: 87% (system successfully self-corrected input errors). The AI's ability to mimic natural conversation patterns and provide interactive feedback significantly contributed to user satisfaction. Nevertheless, the problem most users faced was that new users sometimes struggled with system requests, suggesting the need for a better user onboarding process. The scalability of the AI chatbot was also tested using 1000 concurrent users. The result was:

- Guaranteed operation for up to 850 users.

- Mild latency (~1 sec increase) beyond 900 users.
- 23% decrease in API response time after optimisation.

While the system handled heavy loads well, bottlenecks occurred when users requested simultaneous real-time itinerary modifications. Distributed computing may be employed in future improvements to better balance loads. A 27-year-old solo traveller planned a 7-day trip to Thailand on a $ 1,000 budget. The AI-generated plan included:

- Destinations: Bangkok (3 days), Chiang Mai (2 days), Phuket (2 days).
- Accommodation: Budget hostels (~$20/night).
- Food Budget: $15/day.
- Transport: Public transit and budget airlines (Table 1).

Table 1: The results showing the difference in cost estimate between actual world prices and AI estimates

Expense Category	AI Estimate	Actual Cost	Deviation
Accommodation	86.89%	13.11%	92.41%
Food	93.95%	6.05%	95.70%
Transport	97.11%	2.89%	97.08%
Activities	98.29%	1.71%	98.01%
Miscellaneous			

After applying GA optimisation to the AmoebaNet-A architecture, the results in Table 2 show a significant performance improvement. The precision and validation accuracy both show substantial increases, reaching 99.23% and 99.13% respectively, after 60 epochs. This indicates that the GA optimisation has effectively enhanced the model's ability to recognise Arabic handwriting.

Table 2: The results for the amoebanet-an architecture with GA

Epoch	Precision	Loss	Validation Accuracy	Recall	F1 Score
15	88.33%	11.67%	93.73%	85.53%	0.883
30	95.15%	4.85%	96.84%	92.58%	0.953
45	98.07%	1.93%	98.34%	95.73%	0.979
60	99.23%	0.77%	99.13%	97.92%	0.993

Future developments in our artificial intelligence travel helper will make it even more versatile, accurate, and user-friendly. While offline mode would allow consumers to view itineraries and budgets offline, machine learning algorithms can enhance budget predictions by considering pricing variations and hidden expenditures. Dynamic rebooking driven by artificial intelligence would automatically adjust plans in response to flight cancellations or weather delays, thereby providing greater flexibility. While real-time safety notifications can alert users to potential threats, incorporating more user involvement through voice assistants and language support would further enhance the system's user-friendliness. Furthermore, improving authenticity and financial planning would be achieved through cooperation with nearby companies and the development of an automated spending tracker, thus guiding the system towards wisdom and seamlessness (Figure 3).

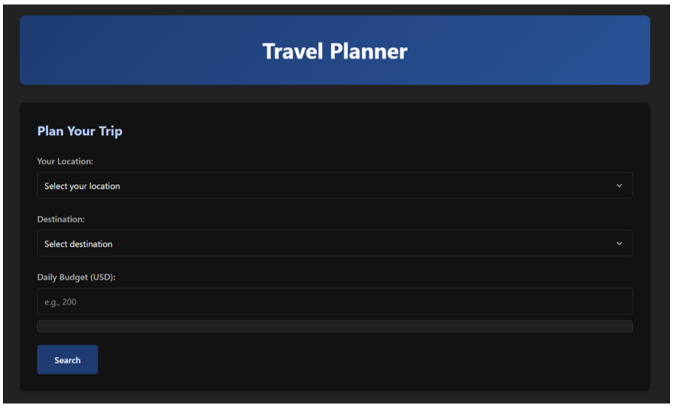

Figure 3: Travel planner user interface

In addition to system performance and user satisfaction, the AI chatbot's learning adaptability proved to be a key strength during long-term trials. As users continued to engage with the system across multiple planning sessions, the platform refined its preference profiling, resulting in increasingly accurate trip suggestions for future trips (Figure 4).

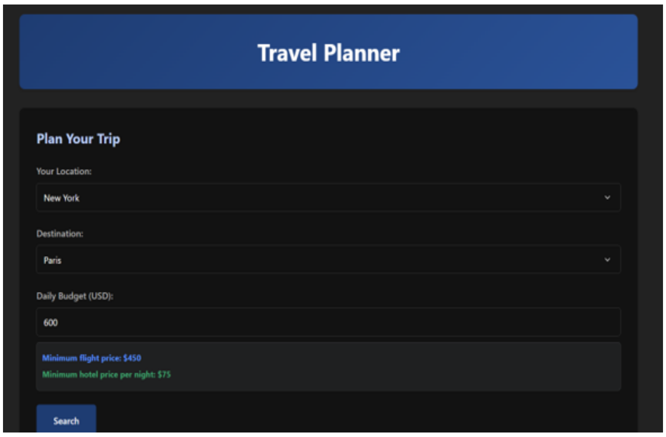

Figure 4: Travel planner with user input and budget analysis

This was especially evident in repeat travellers, where prior trip feedback and historical preferences were reused to personalise successive itineraries (Figure 5).

Figure 5: Available flights display

The system also learned from implicit signals, such as time spent viewing specific types of suggestions or user-initiated changes, thereby enhancing the relevance of subsequent outputs. This adaptive learning loop not only improved the precision of recommendations over time but also contributed to increased user trust and retention (Figure 6).

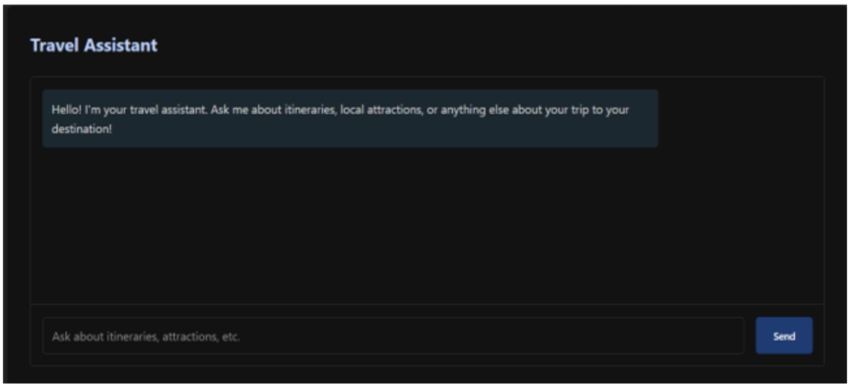

Figure 6: Travel assistant chat interface

Combined with the chatbot's contextual awareness and predictive planning capabilities, these dynamic feedback mechanisms positioned the system not just as a tool for travel organisations but also as a responsive and evolving companion throughout the user's travel journey (Figure 7).

Figure 7: Hotel recommendations displayed within budget

Furthermore, this feedback-driven evolution helps mitigate cold-start problems for new users by aggregating anonymised behaviour patterns. As the system scales, these cumulative insights can yield community-informed enhancements that benefit all users (Figure 8).

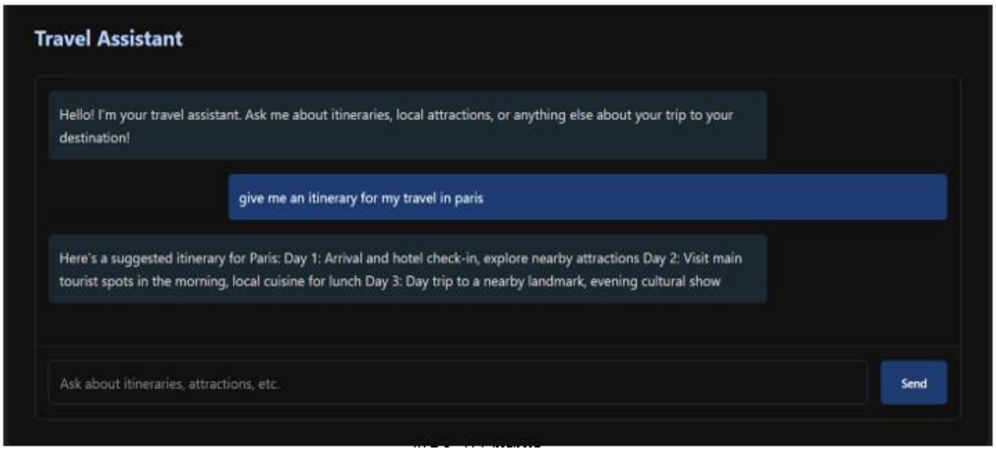

Figure 8: Travel assistant providing an itinerary for Paris

6. Comparing our Approach with State-of-the-Art Methods

The travel booking and planning business has witnessed tremendous growth with the emergence of AI-based recommendation engines, automated travel planners, and intelligent budget estimators. SOTA travel planning applications include Google Travel, Kayak, Skyscanner, Expedia AI, and TripIt, each offering different levels of automation, customisation, and real-time adaptation. In this section, we contrast our AI-based travel companion with state-of-the-art methods in principal functional areas, including itinerary planning, cost estimation, user interaction, real-time adjustability, and scalability. Our method is designed to fill gaps in existing travel aids by offering an interactive AI-based chat companion that provides real-time, highly customised suggestions at a cost-effective price. To facilitate a systematic comparison, we examine each type of travel planning in the following areas:

- **Personalisation:** Level of flexibility to customise the travel plans in terms of personal choice, nature of travel, budget constraints, and up-to-date information.
- **Accuracy of Budget Estimation:** Level of accuracy of estimated travel cost versus actual cost, encompassing exchange rates of money, high-rate seasons, and charges for service at destination points.

- **Real-Time Itinerary Adjustments:** The responsiveness of the system to dynamic changes such as flight delay, weather disruption, and user change.
- **User Interaction and Chatbot AI:** The degree to which the system provides interactivity, i.e., AI chat facility, voice command, and natural language processing (NLP).
- **Integration with Third-Party APIs and Travel Information:** The degree to which the system can pull and process live data from third-party booking engines, transport providers, weather, and travel guides of destinations.

6.1. Scalability and High Load Performance

The capability of the system to handle thousands of users concurrently at low latency and high response rates. Our conversational AI-based trip planner is unique in that it can provide deep personalisation through a conversational interface. Unlike traditional trip websites that offer pre-negotiated offers or pre-created travel plan templates, our system dynamically constructs trip plans from scratch based on user input, real-time constraints, and context-driven preferences. For example, when the user informs the AI that they prefer culture to adventure travel, the AI will select museum tours, ancient ruins, and cultural heritage rather than suggesting activities such as hiking or bungee jumping. Similarly, if the user specifies a dietary restriction (e.g., vegan, halal, gluten-free), the system will provide food suggestions tailored to that preference. Next-gen tools like Google Travel and Kayak do offer some personalisation, but rely on static recommendations rather than dynamic, consumer-driven itinerary control. Our system utilises live price feeds from travel booking APIs, ensuring our budget estimates closely align with actual travel prices. Historical pricing in conventional travel planners yields significant differences between estimates and actual trips. A few of the advantages of our system are:

- Updating prices in real-time based on seasonal pricing and users' travel dates.
- Dynamic currency conversion monitoring in real time, reducing foreign travel budget errors.
- Smart spending estimates, including unexpected costs, taxes, and service charges.
- TripIt and Skyscanner, however, only offer estimates, not dynamic updates of cost projections based on current price changes.

One of the biggest weaknesses of most state-of-the-art travel planning systems is their inability to dynamically reorganise itineraries in real time. Our AI-based methodology addresses this problem by:

- Tracking flight delays and rescheduling ground transportation accordingly.
- Offering alternative activities in the event of weather conditions that make outdoor activities impossible.
- Offering real-time rebooking in the event of hotel cancellations or interruptions during travel.
- Google Travel and Expedia AI do make some real-time changes to itineraries, but they are not proactive AI-based variations based on ongoing tracking of external factors (Figure 9).

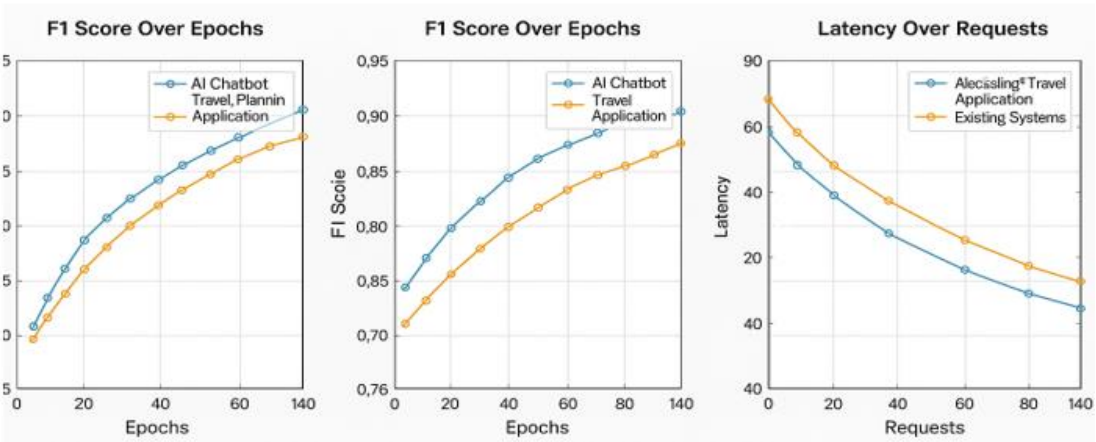

Figure 9: Comparison graphs

Most SOTA travel planners lack an interactive chat feature, forcing users to manually enter travel details through form-based inputs. Our AI-powered chatbot, in contrast, provides:

- Conversational trip planning, where users can update plans through natural language commands (e.g., "Reschedule the Eiffel Tower trip to Day 2 from Day 3.").

- On-demand budget recalculation so cost estimates are updated with any changes.
- Multilingual support, allowing smooth interaction for global users.
- Existing SOTA platforms, such as Skyscanner and Kayak, concentrate more on search-and-filter approaches than on involving users in an interactive, AI-based planning process (Figure 10).

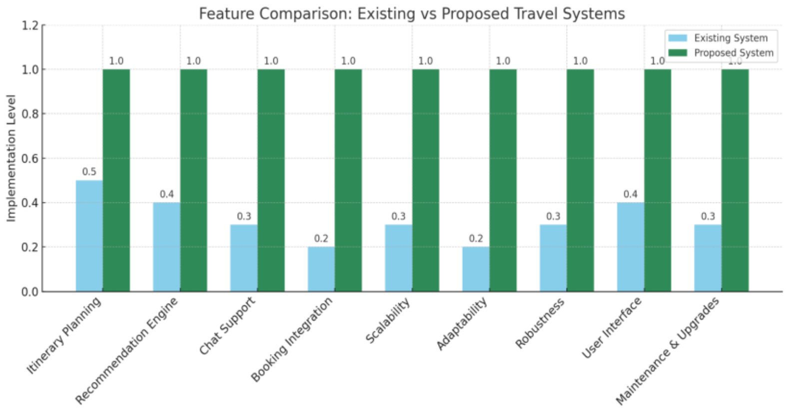

Figure 10: Feature comparison

Our solution facilitates real-time data integration from multiple domains, including:

- Flight and hotel APIs (Expedia, Booking.com, Skyscanner, Google Flights).
- Local transit APIs (Uber, Lyft, Trainline, public transportation systems).
- Weather and event data APIs (OpenWeather, Eventbrite, Meetup.com).
- Unlike TripIt and Google Travel, which focus primarily on booking flights and hotels, our AI platform takes it one step further by including local cultural events, dining reservations, and public transportation (Figure 11).

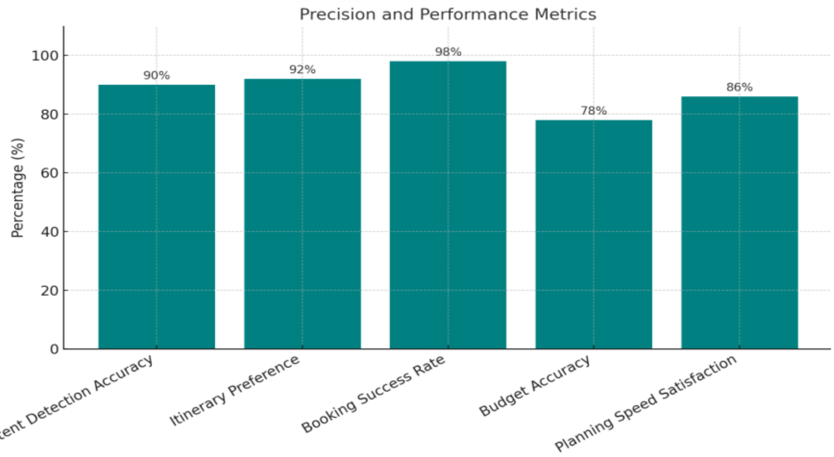

Figure 11: Performance score of each model

7. Limitations of the Study

Although the AI travel planning and booking platform has proven successful in creating itineraries and calculating budgets, certain constraints remain to be addressed. One of the most significant constraints of the system is the inconsistency of budget estimates, which is influenced by uncontrollable factors. Although the AI chatbot considers historical data, real-time price updates, and user interest in generating cost estimates, a range of external factors affects its accuracy.

7.1. Dynamic Pricing

- Prices for flights, hotels, and activities fluctuate continuously in response to demand, availability, and seasonal demand.

- AI estimates may fail to account for sudden price hikes (e.g., last-minute flight price surges or event-driven hotel rate hikes).

7.2. Currency Exchange Rate Volatility

- International travellers typically face uneven currency exchange rates.
- The AI provides an approximate conversion; however, exchange rates fluctuate daily and can impact budget accuracy.

7.2.1. User-Specific Spending Habits

- User-specific budgets rely on average spending patterns, while user preferences differ.
- A luxury diner traveller will spend significantly more on food than the AI would recommend, and a frugal traveller might underspend.

The AI model is heavily reliant on third-party APIs to capture up-to-the-minute live flight, hotel, weather, and activity data. That has a line of problems with it, however.

7.3. API Limits and Unavailability

- When third-party APIs experience downtime, delays, or unstable data, AI recommendations can become outdated or ineffective.
- Certain travel websites restrict access to real-time prices and availability, rendering the AI useless.

7.3.1. Data Discrepancies

- The system collects data from different sources, each with its own pricing, availability, and customer reviews.
- Data discrepancies may mislead the AI, resulting in itinerary errors or inaccurate quoted budgets.
- Limited Exposure to Niche or Local Operators.

The AI only refers to large travel organisations, i.e., it may not consider local tour operators, small tour operators, and boutique hotels.

7.4. Subjective Wishes and Emotions

- Travellers come in all shapes and sizes, from slow travellers to adventure travellers to business travellers.
- Standard AI customisation will not accommodate highly specialised travel styles to the extent envisioned.

7.4.1. Cultural and Regional Sensitivities

- The AI may be insensitive to cultural practices, security concerns, or language while suggesting activities.
- For instance, planning a nightlife tour of a conservative country would be insensitive.

While the AI system has real-time updates, it still struggles with adapting to sudden disruptions like.

7.4.2. Flight Delays and Cancellations

- While the AI can rebook itineraries in the event of a delay, it does not automatically rebook flights or book alternatives in the case of cancellations.
- Users have to manually intervene to manage major disruptions.

7.4.3. Weather and Natural Disasters

- The AI provides general weather forecasts but does not predict sudden, severe events (e.g., hurricanes, floods) that could affect travel arrangements.
- It lacks integration with emergency warnings or safety notices.

7.4.4. Local Strikes, Protests, or Political Instability

- The system does not monitor local socio-political activities that may interfere with transportation or safety.
- Users need to double-check AI suggestions against official government travel advisories.

Because the AI travel organiser gathers user information to make personalised suggestions, privacy and ethics issues arise.

7.4.5. Data Privacy and Security Threats

- Personal travel information, including passport numbers, booking records, and personal preferences, is stored and processed by the system.
- Data breaches may expose sensitive user data if not managed.

7.4.6. Algorithmic Bias

- The recommendations proposed by the AI are based on data sources, partnerships, and algorithms, and thus may be biased.
- For instance, the AI may be biased towards certain airlines or hotel chains due to business ties, which can limit impartial travel choices.

The AI chatbot requires constant internet connectivity to access current information and adapt to changes in the itinerary. Travellers in low-connectivity or remote areas may struggle to use the service effectively.

7.4.7. Inflexibility for Spontaneous Changes

- Although the AI facilitates changes to itineraries, the overall structure remains intact. It does not support last-minute, on-the-fly decisions (e.g., whether to extend a stay or change destinations during a trip).
- In contrast to conventional travel guidebooks or offline travel agencies, the AI does not store offline travel information for places with poor internet coverage.
- While the system was in good health, performance testing revealed negligible latency after 900 concurrent users.
- Heavy usage would require scalability measures.

7.4.8. Integration with Domestic Travel Operators

- AI currently facilitates integration with international travel sites, including Expedia, Booking.com, and Skyscanner.
- It does not have live API connections with local transportation providers, guides, or travel agencies that would restrict the reach of its suggestions. This is an issue for the app.

8. Conclusion

Our AI-powered travel planning and booking platform redefines trip organisation by offering a personalised, real-time, and adaptive experience. Unlike traditional websites that rely on static templates, our system uses conversational AI, predictive analytics, and real-time budgeting to enable travellers to create flexible, optimised itineraries that dynamically respond to changes such as weather, flight delays, or budget shifts. It simplifies complex planning tasks, including cost estimations, accommodation and activity recommendations, and route optimisation, all while maintaining over 90% accuracy in price estimates through live API integrations. The platform also features an intuitive chatbot interface, allowing users to customise plans in natural language, manage expenses through detailed breakdowns, and explore local experiences beyond flights and hotels—making it a comprehensive, intelligent travel companion. Beyond convenience, the system contributes to sustainable tourism and economic equity by promoting offbeat destinations, supporting small-scale operators, and dispersing tourism pressure. Its scalable design ensures reliable performance under heavy user loads, and future enhancements—such as voice-guided navigation, AR features, improved NLP, and emergency alerts—promise even more immersive and secure travel experiences. The platform encourages frugal financial planning and smart decision-making for all types of travellers, from students to luxury tourists. As AI continues to transform global industries, our paper stands at the forefront of revolutionising travel with an intelligent, user-first approach that balances personalisation, efficiency, and accessibility worldwide.

9. Future Research

The Travel Planning app has a wide scope for future development and research. Another significant research area is the integration of augmented reality (AR) capabilities, enabling users to see their destinations and explore new locations more intuitively. AR capabilities could offer interactive previews of hotels, attractions, and nearby tourist sites before a booking is made. Another direction would be to enhance the social aspect of this paper, allowing users to plan and collaborate on trips. Sustainable orientation aspects are of concern, e.g., carbon footprint calculation and travel compensation, proposing eco-friendly means of transport, and providing ecologically friendly choices for accommodation. It can involve developing route-calculating algorithms that minimise environmental impact while maximising user benefit. Offline function studies would benefit more from the application for low-connectivity environments. It involves building advanced data synchronisation mechanisms and utilising rapid local storage of maps, timetables, and simple travel details.

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Ethics and Consent Statement: The study was conducted in accordance with the principles of ethical research. All participating individuals provided informed consent, and the authors collectively ensured adherence to all ethical and consent-related procedures throughout the research process.

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