ARTIFICIAL INTELLIGENCE

Personalized Travel Recommendation and AI Itinerary Planning for Mobile Applications: A Literature Review

Shraddha Manik Pethkar, Mrunal Laxman Saymote, Priyanka Santosh Arate, Aditya Nilesh Vibhute, Pragati Sachin Chiknis

Department of Computer Science & Engineering, Sanjay Ghodawat Institute, Atigre, Kolhapur, Maharashtra, India

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Abstract

Planning a trip is not just choosing a place. A traveller also has to think about interests, number of days, budget, weather, travel time and the order of places to visit. Today, people check these things on different websites and apps, which takes time. This paper reviews existing research on personalized travel recommendation, selection of tourist places, itinerary making, route planning and the use of large language models (LLMs) for trip planning. The studies use methods such as collaborative filtering, machine learning, neural networks and optimization. One common finding is that suggestions are better when the user's preferences are used along with current details like location, season, weather and budget. Another finding is that a plan must be practical, which means distance, time limits and the order of visits must be checked. LLMs let users ask for a trip in simple language, but their answers must still be checked with correct data. Most studies solve only one part of travel planning. So this paper points out the need for one mobile app that combines destination search, itinerary help, budget estimate, weather, maps, trip saving and a chatbot.

Keywords: artificial intelligence; context-aware recommendation; itinerary generation; mobile application; travel recommender system

1 Introduction

There is a lot of travel information on the internet. Websites and apps show places to visit, hotels, transport and reviews. But this information is spread over many services. A traveller may search for places on one app, check the cost on another, see the weather on a third, and then make the daily plan by hand. The final plan may need to be saved somewhere else again. Switching between so many tools wastes time and some details can be missed.

A travel recommender system helps by suggesting places that match what the user needs. It can use the type of place, ratings, earlier searches, location, free time, companions and budget. This is important because one place is not good for everyone. For example, an outdoor place is a bad choice in heavy rain, or when the visitor has only two or three hours.

Artificial intelligence has given a new way to plan trips. Using a large language model (LLM), a user can write the trip details in normal language and get a day-wise plan. But a well-written answer is not always a plan that works. We still need to check whether the places are open, whether the travel time is realistic, and whether the plan fits the days and the budget. For this reason, many recent studies combine language models with proper travel data and optimization methods.

This paper reviews studies on personalized travel recommendation and itinerary planning and lists their limits. It also explains how our capstone project, "AI-Based Travel Recommendation App," tries to bring the main planning steps into one mobile app. The app includes destination search, personalized suggestions, AI itinerary, chatbot, budget estimate, weather, maps, trip saving and PDF export.

The main contributions of this paper are: (i) a review of 17 studies grouped into three themes; (ii) a discussion of their methods, benefits and limits; (iii) the need for a more complete mobile travel app; and (iv) a short outline of a mobile app that responds to the gaps found. The rest of the paper covers background, literature review, comparison, research gap, a proposed application, future research directions and conclusion.

2 Background and scope of the review

2.1 Recommendation approaches in tourism

Travel recommendation methods are of three main types. Content-based methods match features of a place, such as its type, cost or activities, with the user's interests. Collaborative filtering uses the choices or ratings of users who behave in a similar way. Matrix factorization is a common technique for finding patterns in such data. Hybrid methods mix two or more of these to reduce the weakness of a single method.

Tourism brings some extra problems. A person may visit a place only once or twice, so very little history is available. A good suggestion also depends on season, weather, group size, companions and budget. Context-aware systems use these details. Sequence models such as LSTM (long short-term memory) networks can also learn the order in which tourists usually move between places.

2.2 Itinerary planning as a constrained problem

Choosing places is only the first step. The places must then be arranged in a schedule that fits opening hours, travel time, free time and budget. Researchers often treat this as an orienteering problem, where the goal is to cover as many useful places as possible within the limits. Heuristics and mathematical optimization are used to find a good route. Planning for many days is harder because the places must be divided across the days.

2.3 Scope and review questions

This review covers 17 studies published from 2020 to 2024. Most are journal or conference papers, and one of the LLM studies [16] is a preprint. They are discussed under three themes: context-aware and personalized recommendation; place recommendation and itinerary generation; and travel planning with language models. For each study we note the approach, the contribution and the limits that matter for a mobile app.

Booking systems, price comparison sites and tools only for transport routes are outside the scope. The focus is on recommendation, itinerary planning and AI help in one traveller-facing app. Three questions guide the review. RQ1: Which recommendation and planning techniques have been used in recent travel research? RQ2: What problems come up when these methods are used in a real mobile app? RQ3: What is still missing that our project can address?

2.4 Key terms

A point of interest (POI) is a place that a tourist may want to visit, such as a museum, beach or temple. Cold start means that the system has little or no history for a new user or a new place. Context-aware recommendation uses extra details such as weather, season and budget. An orienteering problem is the task of choosing and ordering places to get the most benefit within a time or budget limit. A large language model (LLM) is a model trained on a large amount of text that can read and write natural language.

3 Literature review

3.1 Context-aware and personalized tourism recommendation

These studies look at how a system can decide which places to recommend. They range from surveys to methods based on similarity, patterns, machine learning and collaborative filtering.

Renjith et al. [1] reviewed how context-aware travel recommenders have developed over time. They discuss the features, algorithms and evaluation methods used. The work shows that a travel system should consider the traveller's situation along with general interests. Since it is only a review and not an application, developers still have to choose datasets, methods and evaluation measures.

Kolahkaj et al. [2] proposed a hybrid method to recommend e-tourism packages. It uses asymmetric similarity and sequential pattern mining to include changing context. This helps when both interest and current situation affect the choice. However, it needs enough context and sequence data, which is hard to get for new users or less visited places.

Yoon and Choi [3] presented R2Tour, a real-time tourism recommendation system. It uses the tourist profile together with weather, temperature, rainfall, season and location to suggest nearby places. Tested on data from Jeju Island, it shows that current context is useful. Using it in another region needs good local data.

Nan et al. [4] built a personalized tourism recommendation system using data mining and collaborative filtering. It works well when enough user data is available. But it has the cold-start problem, which means a new user or a new place has little or no history.

Massimo and Ricci [5] discussed what makes a recommender system effective for tourists and studied next-place recommendation in a case study. They stress that tourism has special conditions and that systems should be judged by real travel needs, not only by prediction accuracy.

Hamid et al. [6] reviewed smart tourism recommendation systems and the role of data management. The review is broad, so a developer still has to decide which services and techniques suit a particular app.

Taken together, these studies agree that context matters and that past history alone is not enough. Their common weakness is the need for good data, especially for new users and less visited places.

3.2 Place recommendation and itinerary generation

The next studies go beyond choosing single places. They arrange places into routes or full itineraries using place selection, trajectory learning, cross-media data, reinforcement learning and traffic-aware optimization.

Ji et al. [7] studied personalized one-day itineraries, taking into account how tourist places are spread in space. Their two-stage method uses an improved artificial bee colony algorithm and data envelopment analysis. It shows why location matters, but it focuses on optimization and not on the other services a travel app needs.

Halder et al. [8] proposed an itinerary method that selects and prunes places according to personal preferences. Cutting down the number of candidate places makes planning faster, especially in big cities. A real system still needs reliable place data and limits such as opening hours, travel time and budget.

Beraldi et al. [9] built a decision support system for trips. A neural network finds the link between users and place categories using social media data, and an optimization part makes the itinerary within time and budget limits. It shows the benefit of combining preference estimation with route planning, but the result depends on the quality of the social media data.

Mou et al. [10] developed a route model using trajectory encoding, LSTM and temporal attention. It learns movement patterns from past tourist trajectories. The problem is that new users do not have enough history for personalization.

Lu [11] studied smart tourism recommendation using cross-media data and neural networks. Combining different types of data can help, but the results depend on how complete and consistent the data is.

Gao et al. [12] used self-supervised representation learning for trip recommendation. It learns patterns from place sequences and needs fewer manually labelled examples. The results still depend on the training data and may not carry over to other users and locations.

Dalla Vecchia et al. [13] used deep reinforcement learning to recommend sequences of attractions with sustainable tourism in mind. It uses place and time context, so the plan can consider how visitors are spread out as well as personal interest. It needs suitable data, a careful reward design and clear evaluation.

Ding et al. [14] proposed a two-stage optimization model that considers uncertain traffic time. This is important because travel time is not fixed and traffic can ruin a plan. The model depends on traffic data and assumptions that can differ between cities.

These studies show that choosing places and arranging them in order are two connected problems. They handle limits such as time, budget, distance and traffic well, but most of them need reliable place data, and some need a large amount of past user records.

3.3 Large language models and travel planning

Recent work checks whether language models can understand travel requests and make itineraries. Some studies test the planning ability of language agents, and others connect language models with planners or external tools.

Xie et al. [15] introduced TravelPlanner, a benchmark to test language agents on realistic travel planning. It has user requests and reference plans and checks whether the agent can use tools and meet many constraints. The results show that even a fluent agent can fail on complex requests. An answer that sounds good is not always a workable plan.

de la Rosa et al. [16] proposed TRIP-PAL, which links LLMs with automated planning. The language model reads the travel request and a planner makes a plan that follows the rules. The work notes that

plans made directly by an LLM can be inconsistent and can break constraints. The combined approach is more reliable, but it needs structured data and a planning engine.

Ju et al. [17] presented To the Globe (TTG). A fine-tuned language model changes the user's request into a symbolic form, and mixed-integer linear programming then creates the itinerary. The result depends on how correctly the request is converted and on how complete the travel data is.

These studies show that language models make travel requests easier to write, but cannot be trusted alone for plans that must follow strict limits. Pairing the model with a planner or solver is the main way suggested to fix this.

3.4 Overall findings

Three main points come out of these studies. First, context makes recommendations more useful. Weather, season, companions, budget and location can change which place is suitable [2, 3]. Second, methods that depend on past behaviour struggle when history is small. This affects collaborative filtering and trajectory models [4, 10]. Third, a useful itinerary needs proper checks. Optimization studies handle limits such as time, cost, distance and traffic [7, 9, 14], while TravelPlanner [15] shows that an LLM can give a plan that looks fine but does not meet the request. Hybrid approaches [16, 17] fix this by using a planner or solver to check the plan.

The studies also give different kinds of output. Many are algorithms tested on datasets, while some give a demo system [17]. None of them describes one application that brings together destination search, weather, maps, budget estimate and saved plans. This is the main gap discussed later.

4 Comparison and discussion

Table 1 summarizes the methods, contributions and limits of the reviewed studies. It is a general comparison. Results from different datasets and settings should not be treated as equal.

Table 1. Comparison of the reviewed studies.

Ref.	Study	Method / technology	Main contribution	Limitation
[1]	Renjith et al. (2020)	Review of context-aware travel recommenders	Organizes recommendation methods and evaluation approaches.	Does not specify a complete application implementation.
[2]	Kolahkaj et al. (2020)	Context-aware similarity and sequence mining	Uses changing context for e-tourism package suggestions.	Needs contextual and sequential data.
[3]	Yoon & Choi (2023)	Real-time context and machine learning	Considers weather, season, location and tourist profile.	Local data may not transfer to other regions.
[4]	Nan et al. (2022)	Data mining and collaborative filtering	Uses accumulated user information for personalization.	Cold-start and sparse-data problems.
[5]	Massimo & Ricci (2022)	Tourist next-POI recommendation	Discusses tourism constraints and evaluation.	Evaluation methods need further development.
[6]	Hamid et al. (2021)	Smart-tourism systematic review	Explains recommendation and data management in smart tourism.	Broad review rather than a complete implementation.
[7]	Ji et al. (2021)	Artificial bee colony heuristic and DEA	Considers spatial distribution of attractions.	Optimization assumptions and data affect results.

Ref.	Study	Method / technology	Main contribution	Limitation
[8]	Halder et al. (2022)	Personalized POI selection and pruning	Reduces the candidate set for itinerary planning.	Needs reliable POI and preference data.
[9]	Beraldi et al. (2021)	Neural network and optimization	Handles time-window and budget constraints.	Depends on social-media data and model assumptions.
[10]	Mou et al. (2022)	Trajectory encoding, LSTM and attention	Learns sequential tourist movement patterns.	Requires historical trajectory records.
[11]	Lu (2022)	Cross-media data and neural network	Combines different data types for recommendations.	Data coverage and consistency are important.
[12]	Gao et al. (2022)	Self-supervised representation learning	Learns trip patterns with less manual labelling.	Generalization depends on training data.
[13]	Dalla Vecchia et al. (2024)	Deep reinforcement learning	Recommends attraction sequences with sustainability context.	Needs suitable data, reward design and evaluation.
[14]	Ding et al. (2024)	Two-stage stochastic optimization	Considers uncertain travel time caused by traffic.	Needs traffic data and appropriate assumptions.
[15]	Xie et al. (2024)	TravelPlanner benchmark and language agents	Tests agents on complex travel constraints.	Shows that agents may fail to satisfy all constraints.
[16]	de la Rosa et al. (2024)	LLM and automated planning	Combines language understanding with plan validation.	Needs structured data and a planning engine.
[17]	Ju et al. (2024)	Fine-tuned LLM and MILP	Converts natural-language requests into constrained plans.	Depends on request translation and input-data quality.

4.1 Profile of the reviewed studies

Table 2 shows when the reviewed studies were published. Six studies were published in 2022 and five in 2024, which shows growing interest in recent years. By source, fourteen studies [1]–[14] are journal articles, two [15, 17] are conference papers, and one [16] is a preprint. By theme, six studies [1]–[6] deal with context-aware recommendation, eight studies [7]–[14] deal with place recommendation and itinerary generation, and three studies [15]–[17] deal with language-model-based planning.

Table 2. Publication years of the reviewed studies.

Year	Studies	Count
2020	[1, 2]	2
2021	[6, 7, 9]	3
2022	[4, 5, 8, 10, 11, 12]	6
2023	[3]	1
2024	[13]–[17]	5

4.2 Main technique groups

Collaborative filtering [4] uses patterns in existing user activity. It is easy to apply when data is available, but it struggles with new users and new places. Context-aware methods [1]–[3] adjust suggestions to the traveller's situation, but they need reliable context data. Sequence and deep learning methods [10]–[13] can learn the order of visits and combine different data, but often need a lot of past data. Optimization methods [7]–[9, 14] are useful when a plan must follow time, budget and distance limits. LLM-based methods [15]–[17] let users ask in everyday language, and when an LLM is joined with a planner, a checking step can be added. Table 3 sums up these points.

Table 3. Strengths and limits of the technique groups.

Technique group	Strength	Limit
Collaborative filtering [4]	Uses existing user activity; simple to apply.	Cold start; needs interaction data.
Context-aware methods [1]–[3]	Use weather, season, budget and location.	Need reliable context data.
Sequence and deep learning [10]–[13]	Learn visit order; combine data types.	Need a lot of past data.
Optimization [7]–[9, 14]	Follow time, budget and distance limits.	Depend on data and assumptions.
LLM-based and hybrid [15]–[17]	Natural-language input; a planner adds checks.	LLM output can break constraints.

4.3 Data and evaluation

The studies use different kinds of data, such as Jeju Island tourism data [3], social media signals [9] and benchmark planning tasks [15]. Because the data and evaluation methods differ, the results cannot be compared directly. A method that works in one city may not work as well in another. As Massimo and Ricci [5] note, accuracy alone does not show that a recommendation is useful to a tourist. So an app should be tested with the users and destinations it is made for.

4.4 Evaluation measures

Recommendation systems are usually measured with precision, recall, F1 score and normalized discounted cumulative gain. If ratings are predicted, errors such as root mean square error are used. Itinerary systems also need other measures, such as how much of the user's interest is covered, whether time and budget limits are followed, route length and running time. LLM planners can be checked by seeing whether the output meets the constraints in the request, as in [15]. Since each measure shows a different side, a travel app should use a mix of them.

4.5 Common challenges

Some problems appear again and again in the studies. The first is cold start: new users and new places have little history, which limits collaborative and trajectory methods [4, 10]. The second is outdated data. Opening hours, prices and traffic change, so an old plan may not work now [14]. The third is privacy, because personalization uses location and preference data. The fourth is evaluation, since good results on one dataset may not hold on another, and accuracy does not prove that a plan is convenient [5]. The fifth is trust. An LLM can write a fluent itinerary that breaks real constraints [15, 16], so users should be able to tell confirmed information from estimates.

Data access is another problem for student projects and small teams. Large trajectory or check-in datasets may not be available for a region, and commercial services may have usage limits. So methods that need a lot of history are hard to repeat. Our app therefore starts with user-entered preferences and external services, and does not assume a large local travel dataset.

4.6 Trend of the research

The emphasis has changed slowly over the years. From 2020 to 2022, studies mainly worked on context-aware recommendation, semantic and data mining approaches, heuristic optimization and early neural models [1, 2, 4, 7, 9]–[11]. In 2023, more work appeared on real-time context [3]. In 2024, attention moved to reinforcement learning, uncertain traffic and LLM-based planning [13]–[17]. This suggests that future travel systems will mix learned recommendation models, optimization and natural-language interfaces.

4.7 Critical observations

Looking at the studies together, a few points stand out. Most recommendation studies are tested on one dataset or one region, such as Jeju Island [3], so it is not clear how well they work elsewhere. The optimization studies [7]–[9, 14] give clear ways to respect time and budget, but they usually assume that the place data is already correct and complete. The deep learning studies [10]–[13] can learn complex patterns, but they depend on large amounts of data, which small teams may not have.

The LLM studies [15]–[17] change how users give their requests, since a trip can be written in normal language. At the same time, the benchmark results [15] and the hybrid approach [16] show that a language model should not be trusted alone for planning. The hybrid studies [16, 17] suggest a safer design, where the language model understands the request and a planner or solver builds and checks the plan.

Another point is that the studies mostly describe algorithms and give less attention to features that matter in a real app, such as saving trips, showing maps, estimating a budget or exporting a plan. This is why integration is treated as the main gap in this paper.

4.8 Context and constraint factors used

Table 4 lists the context and constraint factors that the reviewed studies take into account. Context factors such as weather, season, companions and budget help decide which place suits a traveller [2, 3, 6]. Constraint factors such as time, budget, visit order and traffic decide whether a plan can really be followed [7, 9, 14]. A complete travel app needs both kinds of factors, because a plan can match the user's interests and still be impossible to follow.

Table 4. Factors considered in the reviewed studies.

Ref.	Factors considered
[2]	Changing context and the order of past choices.
[3]	Weather, temperature, rainfall, season, location and tourist profile.
[6]	Travel companions, trip duration and budget.
[7]	Spatial distribution of attractions.
[9]	Time windows and budget limits.
[14]	Uncertain travel time caused by traffic.

Ref.	Factors considered
[15]	Many constraints in one request, checked with tool use.
[16]	Formal planning constraints checked by a planner.

4.9 Limitations of this review

This review has some limits. It covers only 17 studies published between 2020 and 2024, so other relevant work may not be included. The discussion is based on what each study reports, and no experiments were repeated by the authors. Because the studies use different datasets, regions and evaluation methods, their results are compared only in a general way. Some of the language-model studies are conference papers or preprints, which may change after further review. A wider and more systematic search can be done in future work.

4.10 Answers to the review questions

RQ1 asked which techniques have been used in recent travel research. The studies use collaborative filtering and data mining [4], context-aware methods [1]–[3], sequence and deep learning models [10]–[13], optimization methods [7]–[9, 14], and LLM-based or hybrid planners [15]–[17]. RQ2 asked what problems appear in a practical mobile app. The main problems are the cold-start problem, outdated data, plans that break real limits [15, 16], privacy of user data, limited access to large datasets, and results that do not carry over from one city to another [5]. RQ3 asked what is still missing. The reviewed studies mostly solve one part of the problem, and none of them joins destination search, itinerary planning, budget estimate, weather, maps and trip saving in one app with checks on the generated plan.

5 Research gap

The reviewed work has improved destination recommendation, place selection, route planning, itinerary optimization and conversational help. Still, some issues remain when we look at a complete mobile app.

Many studies focus on one task, such as ranking places, predicting the next place or optimizing a route [7, 8, 10]. Other itinerary methods depend on structured datasets, user history or optimization models [9], which makes suggestions difficult for first-time users [4]. Language models make it easy to describe a trip, but benchmark and hybrid studies show that generated plans may still break real constraints [15, 16]. Also, weather, traffic, availability and costs can change after a plan is made [3, 14].

In practice, a traveller today follows a long manual process. The traveller searches for destinations, reads different websites, compares places by hand, checks the weather in another app, works out an approximate budget, uses a map app for directions, writes the itinerary and saves it in yet another place. Each step needs a different tool, and the user has to join the information together.

In short, the gaps found in the literature are: (1) little support for new users who have no history; (2) plans that can become outdated when weather, traffic or costs change; (3) generated plans that can break time, day or budget limits; (4) methods that solve only one task; and (5) unclear reliability, because users may take generated content as confirmed information. These gaps point to an integration gap, since a traveller may still need separate services for finding places, checking weather, viewing maps, estimating cost and managing trips.

6 Proposed application based on the review

6.1 Overview

To respond to these gaps, our capstone project proposes the AI-Based Travel Recommendation App, a mobile travel companion. It is meant to recommend destinations from the traveller's interests and trip details, create an editable day-wise itinerary, give an approximate budget, show weather and maps, answer travel questions through a chatbot named Atlas, and let users save and export plans as PDF. This section only outlines the design. The app is still under development, and no test results are reported in this paper.

6.2 System architecture

The mobile app is planned with React Native, Expo and TypeScript. The backend uses Node.js and Express.js to handle requests and provide REST APIs. MongoDB Atlas stores user profiles, preferences, destinations, trips, favourites and reviews. Google Gemini supports itinerary generation and the chatbot. Open-Meteo gives weather information, and map and navigation services give locations, directions and multi-stop routes (Figure 1 and Table 5). The backend handles the logic, login and database, and connects to the external services, so the user interface stays separate from the data and services.

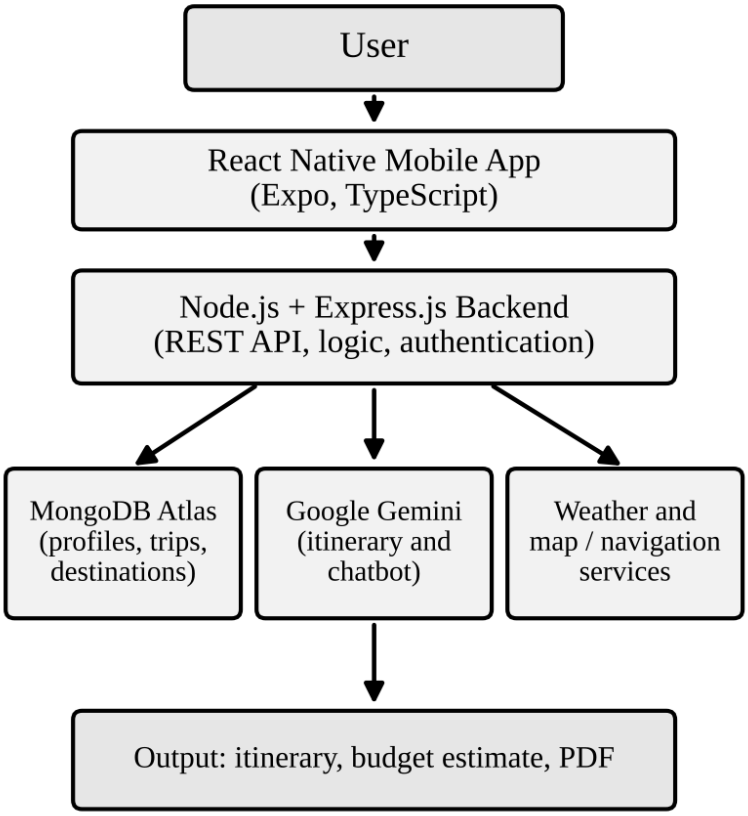


Figure 1. High-level architecture of the proposed AI-Based Travel Recommendation App.

Table 5. Technology stack of the proposed application.

Component	Technology	Purpose
Frontend	React Native, Expo, TypeScript	Mobile screens; collects trip details and shows results.
Backend	Node.js, Express.js	REST APIs, logic and authentication.
Database	MongoDB Atlas	Stores profiles, preferences, destinations, trips and reviews.
AI service	Google Gemini	Itinerary generation and the Atlas chatbot.
Weather	Open-Meteo	Weather information for the travel period.
Maps	Map and navigation services	Locations, directions and multi-stop routes.
Output	PDF generation	Itinerary that users can save or share.

6.3 Planning workflow

The workflow (Figure 2) starts when the traveller enters the destination, days, budget, number of travellers and interests. To reduce the cold-start problem [4], the first suggestions use the preferences entered at registration, and weather for the trip dates is added as extra context [3]. Gemini then prepares a day-wise draft itinerary. Before the result is accepted, the system checks whether the plan fits the number of days, the estimated budget and the order of stops, because generated plans can break such limits [15, 16]. If there is a problem, a revised plan is requested. The traveller can then edit the itinerary, save it, export it as PDF or open the stops on a map. Budget values and AI output are marked as estimates, and users should confirm opening hours, prices and weather before travelling.

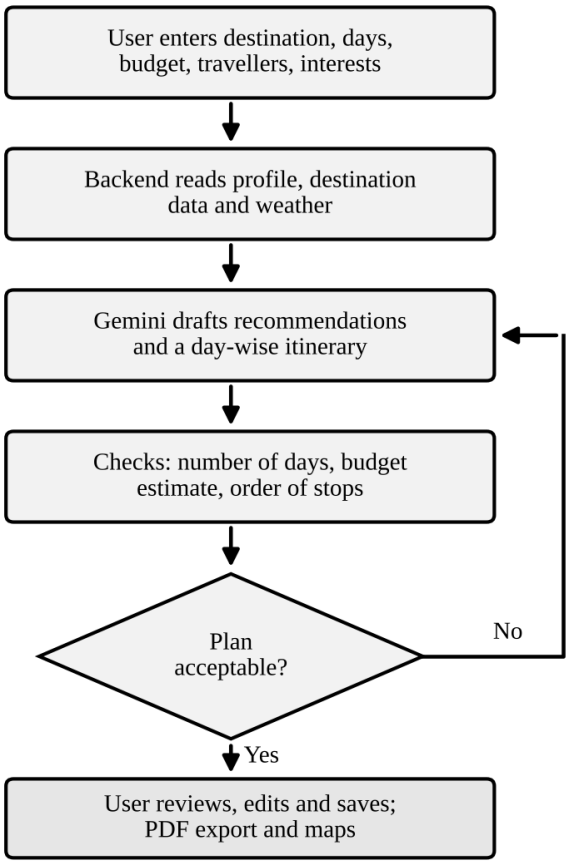


Figure 2. Planning workflow of the proposed application.

6.4 How the application responds to the gaps

Table 6 links each gap found in the literature to the matching design decision.

Table 6. Identified gaps and the proposed response.

Gap	Issue in existing approaches	Proposed response
Little history for new users	Collaborative and trajectory methods need past activity [4, 10].	Collect interests and preferences at registration; give profile-based suggestions.
Changing context	Weather, traffic and costs can change after planning [3, 14].	Get weather during planning and label plans as suggestions.
Plans may break limits	Generated plans can miss days, budget or visit order [15, 16].	Check trip days, budget and stop order; allow user edits.
Methods solve separate tasks	Some systems focus only on ranking or routing [7, 8].	Combine discovery, itinerary, budget, maps and trip management.
Unclear reliability	Users may take generated content as confirmed information.	Label estimates clearly and ask users to review plans before saving.

6.5 Limitations of the proposed work

The design has some limits. AI output, weather and maps depend on outside services, so downtime or usage limits can affect the app. Budget values are estimates and may differ from real prices. In the first version, recommendations are based mainly on matching user-entered preferences and not on a

fully trained recommendation model. The first itinerary checks cover only the number of days, estimated budget and stop order. The app has not yet been evaluated with users, so its expected benefits are not yet shown.

7 Future research directions

The reviewed studies suggest several directions. First, handling the cold-start problem better is still important. Apps can begin with preferences entered by the user and later add collaborative filtering and machine learning ranking as activity data grows. Second, language models should be combined with planners or solvers so that generated plans are checked against real limits, as the hybrid studies [16, 17] show. Third, systems should use fresher data, such as live transport and traffic information and up-to-date opening hours and prices [14]. Fourth, personalization should be built with user privacy in mind, collecting only the data that is needed.

Fifth, evaluation needs more care. Future work should test systems on more than one destination and use several measures together, such as relevance, feasibility of the plan, factual accuracy, ease of use and response time [5, 15]. Finally, practical features such as hotel and flight booking, multilingual and voice-based assistance, built-in maps and better travel-cost prediction can make travel apps more complete for different groups of users.

The review also gives some practical points for people who build travel apps. New users should be asked about their interests and trip preferences at registration, instead of waiting for a history of past trips [4]. Changing details such as weather should be checked when a trip is planned [3]. An AI-generated itinerary should be checked against the number of travel days and the estimated budget before it is shown as a usable plan [15, 16]. Finally, estimated values and AI output should be clearly marked, so that users can tell confirmed information from suggestions and can confirm opening hours and prices before travelling.

8 Conclusion

This paper reviewed research on personalized tourism recommendations, context-aware POI selection, itinerary generation, route optimization and AI-supported travel planning. Across the studies, recommendations are more useful when personal interests are considered together with location, time, weather, budget and trip duration. Creating a workable itinerary also requires attention to distance and time constraints. Language models make it easier for travellers to explain what they want, but structured data and optimization checks are still important for producing practical plans. The proposed AI-Based Travel Recommendation App aims to bring these activities together in one mobile platform. It is designed to support destination discovery, personalized suggestions, AI-assisted itineraries, estimated budgets, weather information, maps, chatbot support and trip management.

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References

[1] Renjith S, Sreekumar A, Jathavedan M. An extensive study on the evolution of context-aware personalized travel recommender systems. *Information Processing & Management*. 2020;57(1):102078. https://doi.org/10.1016/j.ipm.2019.102078

[2] Kolahkaj M, Harounabadi A, Nikravanshalmani A, Chinipardaz R. A hybrid context-aware approach for e-tourism package recommendation based on asymmetric similarity measurement and sequential pattern mining. *Electronic Commerce Research and Applications*. 2020;42:100978. https://doi.org/10.1016/j.elerap.2020.100978

[3] Yoon J, Choi C. Real-time context-aware recommendation system for tourism. *Sensors*. 2023;23(7):3679. https://doi.org/10.3390/s23073679

[4] Nan X, Kanato K, Wang X. Design and implementation of a personalized tourism recommendation system based on the data mining and collaborative filtering algorithm. *Computational Intelligence and Neuroscience*. 2022;2022:1424097. https://doi.org/10.1155/2022/1424097

[5] Massimo D, Ricci F. Building effective recommender systems for tourists. *AI Magazine*. 2022;43(2):209–224. https://doi.org/10.1002/aaai.12057

[6] Hamid RA, Albahri AS, Alwan JK, Al-qaysi ZT, Albahri OS, Zaidan AA, et al. How smart is e-tourism? A systematic review of smart tourism recommendation system applying data management. *Computer Science Review*. 2021;39:100337. https://doi.org/10.1016/j.cosrev.2020.100337

[7] Ji H, Zheng W, Zhuang X, Lin Z. Explore for a day? Generating personalized itineraries that fit spatial heterogeneity of tourist attractions. *Information & Management*. 2021;58(8):103557. https://doi.org/10.1016/j.im.2021.103557

[8] Halder S, Lim KH, Chan J, Zhang X. Efficient itinerary recommendation via personalized POI selection and pruning. *Knowledge and Information Systems*. 2022;64:963–993. https://doi.org/10.1007/s10115-021-01648-3

[9] Beraldi P, De Maio A, Olivito F, Potrino G, Straface I, Violi A. A decision support system for trip tourism recommendation. *International Journal of Transport Development and Integration*. 2021;5(1):69–80. https://doi.org/10.2495/TDI-V5-N1-69-80

[10] Mou N, Jiang Q, Zhang L, Niu J, Zheng Y, Wang Y, et al. Personalized tourist route recommendation model with a trajectory understanding via neural networks. *International Journal of Digital Earth*. 2022;15(1):1738–1759. https://doi.org/10.1080/17538947.2022.2130456

[11] Lu J. Personalized recommendation algorithm of smart tourism based on cross-media big data and neural network. *Computational Intelligence and Neuroscience*. 2022;2022:9566766. https://doi.org/10.1155/2022/9566766

[12] Gao Q, Wang W, Zhang K, Yang X, Miao C, Li T. Self-supervised representation learning for trip recommendation. *Knowledge-Based Systems*. 2022;247:108791. https://doi.org/10.1016/j.knosys.2022.108791

[13] Dalla Vecchia A, Migliorini S, Quintarelli E, Gambini M, Belussi A. Promoting sustainable tourism by recommending sequences of attractions with deep reinforcement learning. *Information Technology & Tourism*. 2024;26(3):449–484. https://doi.org/10.1007/s40558-024-00288-x

[14] Ding Y, Zhang L, Huang C, Ge R. Two-stage travel itinerary recommendation optimization model considering stochastic traffic time. *Expert Systems with Applications*. 2024;237:121536. https://doi.org/10.1016/j.eswa.2023.121536

[15] Xie J, Zhang K, Chen J, Zhu T, Lou R, Tian Y, et al. TravelPlanner: A benchmark for real-world planning with language agents. *In: Proceedings of the* 41st International Conference on Machine Learning (ICML). Proc Mach Learn Res. 2024;235:54590–54613.

[16] de la Rosa T, Gopalakrishnan S, Pozanco A, Zeng Z, Borrajo D. TRIP-PAL: Travel planning with guarantees by combining large language models and automated planners [preprint]. *arXiv*:2406.10196. 2024. https://doi.org/10.48550/arXiv.2406.10196

[17] Ju D, Jiang S, Cohen A, Foss A, Mitts S, Zharmagambetov A, et al. To the Globe (TTG): Towards language-driven guaranteed travel planning. In: *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*; 2024. p. 240–249. https://doi.org/10.18653/v1/2024.emnlp-demo.25