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AI-Powered Personalized Smart Travel Assistant with Dynamic Decision Intelligence

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Abstract

The traditional navigation systems focus primarily on finding the shortest route, ignoring many things such as weather, traffic, accidents, parking and preferences of travelers. The recent work uses for the purpose of personalized trip planning various state-of-the-art technologies, such as machine learning, predictive analytics, NLP, LLMs and real-time data. The existing systems, however, are all built on a single task, rely on external APIs, and often do not provide any privacy considerations or validation of the real-world. This paper provides review of eight studies published in 2023-2026, identifies six research gaps. The paper proposes design of an AI-based smart travel assistant that is capable of taking into account external factors for the purpose of effective decision-making. The designed system features a data integration layer, a prediction engine, a multi-criteria decision processor and a module providing explanations of decision made. An implementation plan and evaluation process are presented. This paper contributes to literature by providing a grounded design of such a system and discussing research agenda for further study of the topic. The proposed system aims to improve travel efficiency by providing adaptive route recommendations based on changing real-time conditions and individual traveler preferences. Future work will focus on prototype implementation, real-world testing, and evaluating the system's accuracy, reliability, and personalization.

Keywords: Artificial intelligence, Dynamic decision intelligence, Intelligent route planning, Machine learning, Personalized travel assistant, Predictive analytics, Recommendation system, Real-time data integration, Smart transportation

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I. Introduction

The advent of modern Artificial Intelligence (AI), Machine Learning (ML), the Internet of Things (IoT) and smart city technologies have completely changed the way we travel nowadays. Conventional navigational systems concentrate on finding the shortest route and neglect important factors such as traffic conditions, weather conditions, safety of roads and parking spots as well as user preferences which leads to rather inefficient travel decisions.

The AI-based personalized smart travel assistant with dynamic decision intelligence is composed of AI and applies predictive analytics, recommendation systems and real-time data to offer intelligent and personalized travel recommendations. The technology can evaluate traffic jams, accident notifications, weather conditions, road conditions, parking availability, predicted travel duration as well as historical data about users travelling habits to make recommendations on possible ways and optimal time.

Dynamic decision making can allow users to find safe and efficient routes, decrease unnecessary wait time, optimize the use of resources, and contribute towards more effective and environmentally responsible transportation. The literature reflects a tendency to use LLMs in conjunction with real-time external data sources for providing adaptable, context-specific recommendations instead of relying on static, rule-based planning tools. However, this development has its drawbacks: reliance on third-party APIs is a source of risks due to the potential issues relating to the vulnerability of a single point of failure, and the obscure nature of the suggestions offered by LLMs limits both transparency and trust of users. In the proposed paper, we present three contributions. Firstly, we analyze eight publications on AI-based travel assistance developed between 2023 and 2026 and explore their methodologies, findings, and limitations (Section III). Secondly, we outline six gaps in research based on this analysis (Section IV). Lastly, we introduce a conceptual framework, implementation roadmap, and evaluation plan aimed at addressing these gaps (Sections V–X). Thus, the study is rooted in existing literature.

The proposed framework also emphasizes privacy protection, explainable recommendations, and reliable decision-making under changing travel conditions. It provides a foundation for developing an intelligent travel assistant that integrates multiple data sources to deliver personalized, transparent, and sustainable travel recommendations.

II. Problem Statement and Objectives

A. Problem Statement

Nowdays navigation apps are designed to find the quickest way and often ignore true traffic status, weather, safety on roads, as well as availability of parking. Such approach can lead to delays, fuel wastage, safety issues and overall ineffective travel. Hence, the paper will focus on how the application of AI, predictive analytics and dynamic decision intelligence can facilitate personalized navigation decisions based on real-time traffic, weather, parking availability, road safety and preferences of users.

B. Objectives

1. Study the application of Artificial Intelligence, Machine Learning and Dynamic Decision Intelligence in personalized smart travel assistance.
2. Analyze recent research papers and existing intelligent transportation systems for real-time route planning and personalized travel recommendations.

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3. Examine how real-time data such as traffic conditions, weather, road safety, accidents, parking availability and user preferences can improve travel decision-making.
4. Evaluate the societal impact, sustainability and ethical aspects of AI-powered smart travel systems in enhancing commuter safety, reducing travel time and optimizing transportation resources.
5. Understand the future scope and emerging trends of AI-driven intelligent transportation systems and their role in smart cities and next-generation mobility solutions.

III. Related Work

Eight studies published between 2023 and 2026 were reviewed. The field has moved from static shortest-route navigation through predictive analytics and ML-based planners to LLM-based assistants that use real-time data (Fig. 1). Table I summarises the reviewed studies, which are grouped below by approach.

A. Predictive Analytics and Travel Services

Burugulla [3] used predictive analysis and machine learning to examine booking history, weather trends and travel patterns in terms of travel prediction. The procedures used resulted in better travel predictions, recommendations as well as improved customer experience. Increased volumes of real-time data is necessary and raises privacy issues. On the other hand, Barua and Kaiser [4] offer a microservices-based system that could integrate AI, machine learning and predictive analysis for a travel booking system, minimizing the time taken to make accurate travel predictions, respond to requests and scale operations while increasing costs and dependence on cloud services.

B. LLM-Based Travel Assistants

In the study of Chen et al. [1], TravelAgent is created, a travel assistant built on LLMs that utilizes users' preferences and real-time data to produce an individualized trip itinerary that surpasses the existing solutions; the model requires the data to be accurate and the users' preferences to be well specified. Whereas in the study of Chore et al. [6], LLMs are combined with various technologies such as NLP and ML, along with memory-based customization and real-time APIs, and a multi-agent approach is developed, which allows the creation of personalized recommendations and cuts the time of planning, but reliance on external APIs may lead to outdated information and privacy issues.

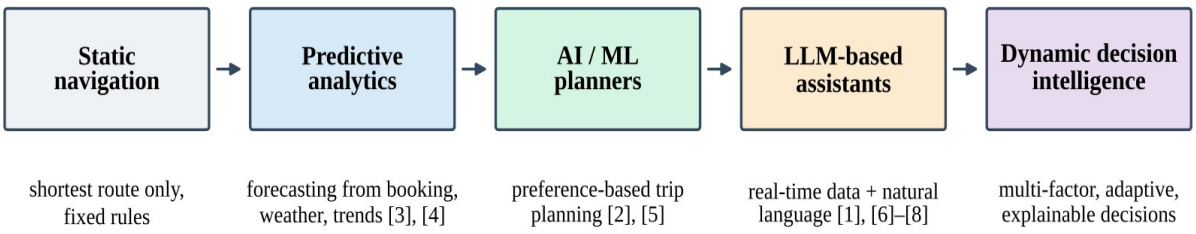


Fig. 1. Evolution of travel assistance, from static navigation to dynamic decision intelligence, with the reviewed studies that represent each step.

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Table

I: Comparative Summary of Reviewed Literature

Ref.	Author / Year	Methodology	Key finding	Limitation
[1]	A. Chen et al. (2025)	LLM-based travel assistant (TravelAgent) using real-time data and user preferences	Better personalized planning and recommendation quality than existing AI travel agents	Depends on accurate real-time data and detailed user preferences
[2]	Dr. Anitha S. et al. (2024)	AI and ML on user preferences, budget and travel history	Reduced planning time; higher user satisfaction	Relies on quality user input and third-party travel services
[3]	J. K. R. Burugulla (2023)	Predictive analytics and ML on booking history, weather and travel trends	Better travel prediction, personalized recommendations and customer experience	Requires large real-time datasets; privacy concerns
[4]	B. Barua & M. S. Kaiser (2024)	Microservices framework integrating AI, ML and predictive analytics	Higher prediction accuracy, faster response, scalability	High implementation cost; dependency on cloud infrastructure
[5]	Kavyashree E. D. et al. (2026)	AI recommendation engine, ML and real-time APIs (weather, maps, hotels, traffic, transport)	Better personalized planning; optimized travel time and budget	Depends on API accuracy and connectivity; outdated data may affect quality
[6]	M. Chore et al. (2025)	LLMs, NLP, ML and memory-based personalization in a multi-agent architecture with real-time APIs	Adaptive recommendations; less planning time; better itinerary quality	Relies on external APIs; may give outdated information; privacy concerns

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[7]	V. S. Kotari et al. (2025)	LLM with Next.js, TypeScript, Convex database and interactive maps	Less planning time; personalized day-wise itineraries; route visualization	Depends on LLM accuracy; lacks complete real-time weather and booking integration
[8]	C. Deshmukh et al. (2025)	Google Gemini API, NLP and Node.js with real-time travel data	Personalized plans and optimized routes; scalable	Depends on internet and API accuracy; limited real-world validation

C. AI and ML Trip Planners

Anitha et al. [2] leverage artificial intelligence (AI) and machine learning (ML) techniques to analyze traveler preferences, budget, and travel history for effective trip planning, stating that the reduction of the planning duration ensures higher satisfaction levels of users, yet the quality relies on the user input and other companies' services. Kavyashree et al. [5] utilize the AI recommendation engine and machine learning in combination with the real-time API for weather, maps, hotels, traffic, and transport information to develop customized journey plans that optimize the time and money used. Quality, however, might be compromised in the case of using outdated information or a weak connection. Kotari et al. [7] developed a smart itinerary planner with the application of large language models (LLM), Next.js, TypeScript, and Convex database, still lacking complete real-time weather forecasts and other booking systems. Deshmukh et al. [8] rely on the Google Gemini API, NLP, and Node.js backend for creating personalized plans and optimized routes by means of up-to-date travel data without practice verification in the real world.

D. Cross-Cutting Observations

Four patterns recur. Most systems depend on external APIs [1], [5], [6], [8] or cloud services [4]. Several raise privacy concerns [3], [6]. Many focus on itinerary generation rather than on route and timing decisions made from several live factors together. And real-world validation is limited [8]. These patterns motivate the research gaps in Section IV.

IV. Research Gaps

The eight studies reveal six gaps that inspire the framework discussed in Section V.

G1. No real-time data integration. The most of the systems use outside APIs for traffic situation, weather, maps and transport information and the performance quality tends to fall when real-time data is unavailable or outdated [1], [5], [6].

G2. No personalization. The current planners make use only of basic preferences and history and do not update their recommendations as per their users' behavior and current events [2], [8].

G3. Dependence on external solutions. Existing solutions in practice often utilize Google Maps, weather APIs, hotel reservation APIs, and other third-party services which renders the system vulnerable to failures in those services [5], [8].

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G4. Absence of dynamic decision-making capability. Most studies are doing research on route planning, or itinerary generation but fail to include real-time components like traffic, weather, accidents, parking, and preferences [1], [7].

G5. Personal privacy and data security challenges. The AI travel assistant gathers information on the user's travel and location but provides little guarantee on the privacy and security of that data [3], [6].

G6. Insufficient real-world testing. Existing solutions have been evaluated through simulations and small datasets, with few solutions tested in the real world on a large scale [8].

Main gap: no reviewed study combines live multi-factor data, personalization, dependable operation without a single external API, privacy handling and explainable decisions in one travel assistant.

V. Proposed Framework

A. Design Principles

The framework addresses the identified gaps in Section IV by providing: a layer for integrating data with validation (G1); adaptive personalization (G2); the use of caching and alternative sources (G3); a decision-making engine that considers all live parameters (G4); data processing that respects privacy (G5); the running of a pilot evaluation (G6). The design is guided by four principles:

- **Contextuality:** each recommendation considers issues relating to traffic, weather, accidents, overall road conditions, parking, road safety and user preferences;
- **Reliability:** the system continues functioning with cached or back-up data when a live source fails, and the user is informed about how current its data is;
- **Understandability:** every recommendation is delivered with a rationale so that users learn to trust it;
- **Awareness of privacy:** both personal and location data is minimized and used with consent only after securely persisting it.

B. System Architecture

The layers of the assistant are depicted in Fig. 2. Data sources go to an integration layer which verifies incoming data and caches it. The prediction module forecasts congestion, travel time, and delay, while the personalization module processes user preferences and history, as well as accepts requests stated in natural language via LLM or NLP systems. The dynamic decision engine evaluates routes and travel times to give their score and order while the explanation interface shows the outcome with explanations and notifications. User feedback will be sent back to the data and personalization layers. The functions of the various supporting technologies are summarized in Table II. This layered architecture enables continuous information exchange between modules, allowing the system to adapt recommendations according to changing road conditions and user requirements. It also supports modular development, easier maintenance, and future integration of advanced AI technologies to improve the overall travel experience.

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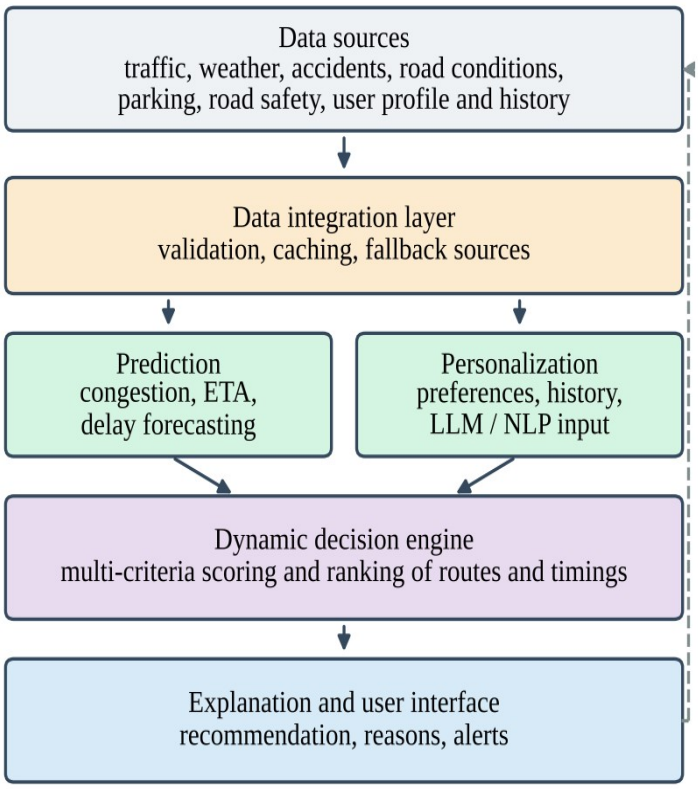


Fig. 2. Proposed layered architecture of the smart travel assistant, with a feedback loop from the interface.

Table II: Technology Roles in the Framework

Technology	**Role in the framework**
AI and Machine Learning	Real-time analysis, prediction and intelligent decisions
Real-time data and IoT	Live traffic, weather and road-safety data through devices and APIs
Smart cities and ITS	Congestion management and better commuter experience
Personalization	Adaptive, user-centric recommendations
Predictive analytics	Forecasting of traffic, delays and travel time
GPS and location	Positioning and route tracking

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C. Data Sources and Integration

The integration layer collects the data that drives each decision. Table III lists the sources considered and how each is used. Incoming data is checked for freshness and plausibility before use, and recent values are cached. This lets the assistant keep working when a source is slow or unavailable, which addresses the single-point-of-failure problem identified in [5], [8].

Table III: Data Sources and Their Use

Data source	**Use in the system**
Traffic congestion	Route choice; estimated travel time
Weather	Safety; delay and timing advice
Accident alerts	Avoiding blocked or risky roads
Road conditions / safety	Safer route ranking
Parking availability	Destination planning; arrival time
User history and preferences	Personalization of ranking

D. Prediction and Personalization

The module of prediction is utilizing the method of ML and predictive analytics to forecast congestion in a way similar to that applied in [3] and [4]. Thus, it becomes possible for the assistant to give advice regarding departure time and a route. The module of personalization creates a user profile based on their preferences and their travel history. For the personalization module to function correctly, access to feedback is needed and the user profile built using the method depicted in [2] and [6] should be updated.

E. Dynamic Decision Engine

The proposal is unique due to the decision engine (G4). As indicated in Fig. 3, the decision engine analyzes real-time factors and user preferences, applies a multi-criteria scoring approach where all routes and departure times are assigned scores, and ranks them. Weights are defined according to the user profile. For example, a commuter is expected to weigh time more, while a visitor may consider safety and parking more important. Table IV presents some user profiles. Moreover, the decision engine registers which factors shaped the ranking in order to make the reasoning process transparent in the interface.

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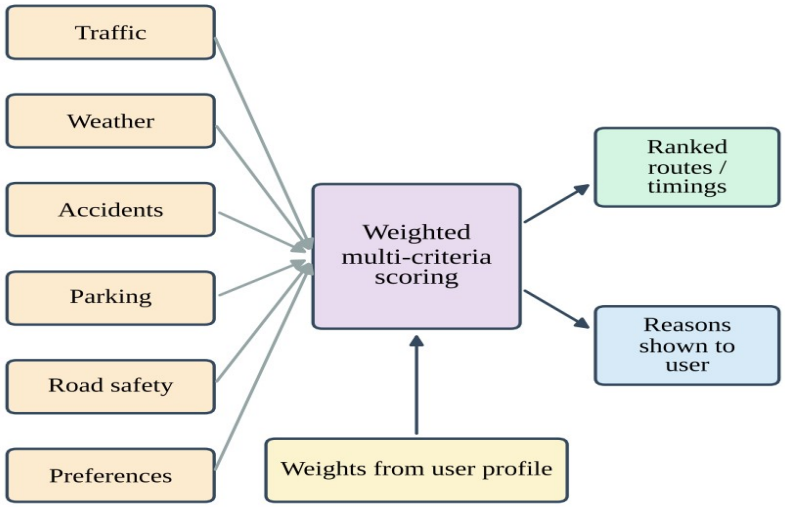


Fig. 3. Dynamic decision engine: live factors and user weights produce ranked options and the reasons for them.

Table IV: Example User Profiles and Factor Weights

Profile	Time	Safety	Parking	Cost
Daily commuter	High	Medium	Medium	Low
Safety-first traveller	Medium	High	Low	Low
Visitor / tourist	Medium	Medium	High	Medium
Budget traveller	Low	Medium	Medium	High

F. Reliability and Privacy

As illustrated in Fig. 4, the assistant gathers data from live feeds, and if there are issues with the timeliness of the data, then it accesses the data stored in its cache and provides results with an accompanying note indicating the correctness of the information used. Both reliability and transparency are equally important: users should be informed if a suggestion is based on outdated data. With respect to privacy, the data needed for the decision should be collected only, the histories should be securely stored and kept only for a specified period of time, and the users should retain control over the data they choose to share.

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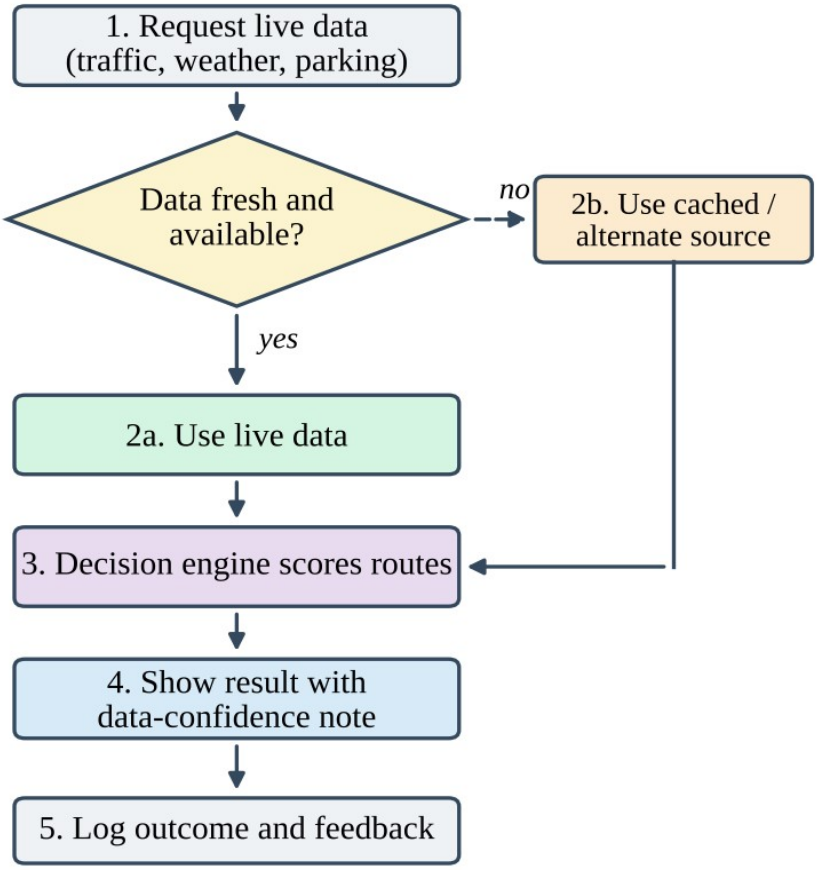


Fig. 4. Data-reliability workflow: live data when available, cached or alternate data otherwise, with a confidence note.

VI. Implementation Roadmap

Being that the framework is a design, Fig. 5 provides the steps that will contribute to its construction and testing. For phase 1, which concerns a literature review and gap analysis, the work reported in this paper is done. Phase 2 requires the development of a data level involving API integration, validation, caching, and a fallback mechanism. Phase 3 anticipates the development of predictive and personalizing models. Phase 4 involves the incorporation of a decision-making engine and an explanation interface. Phase 5 involves performing a pilot project and evaluating its results as per the criteria indicated in Table VI.

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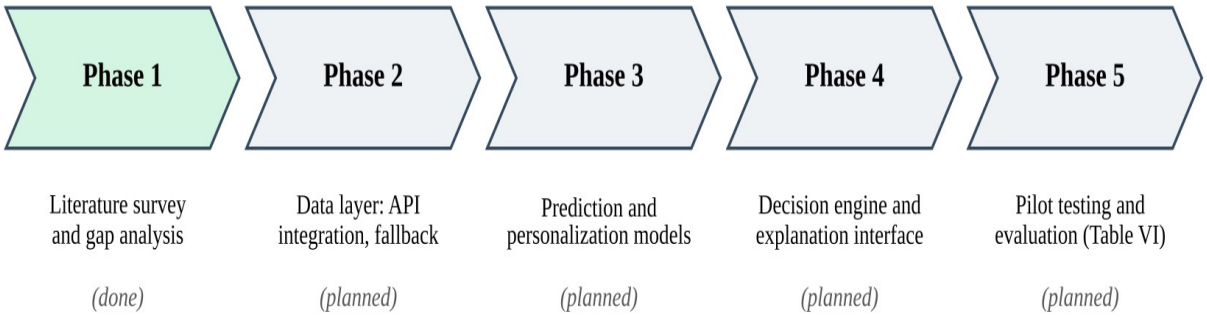


Fig. 5. Proposed implementation roadmap. Phase 1 is complete; later phases are planned.

VII. Comparative Analysis

Figure 6 shows the comparison between the studies reviewed and the suggested framework on seven attributes identified from Table I: predictive ML, using either LLM or NLP, gaining insight from real-time data, personalization, optimization of routes, preserving privacy, and independence from the only operation via one API. A tick shows whether or not the study in question employs this attribute, while the tilde indicates partial implementation of the capability. The marking process is qualitative and does not involve the information presented in the methods, outcomes, and limitations descriptions provided in Table I; the evaluation of the suggested framework is made based on how it is designed rather than on its performance.

The comparison evaluates existing studies and the proposed AI-powered smart travel assistant using seven important features. These include machine learning, NLP/LLMs, real-time data, personalization, route optimization, privacy protection, and reduced dependency on a single API. It helps identify the strengths and limitations of current travel assistance systems. The proposed framework aims to combine these features to provide more reliable, personalized, and efficient travel recommendations. The evaluation is based on the system design rather than actual testing or performance results.

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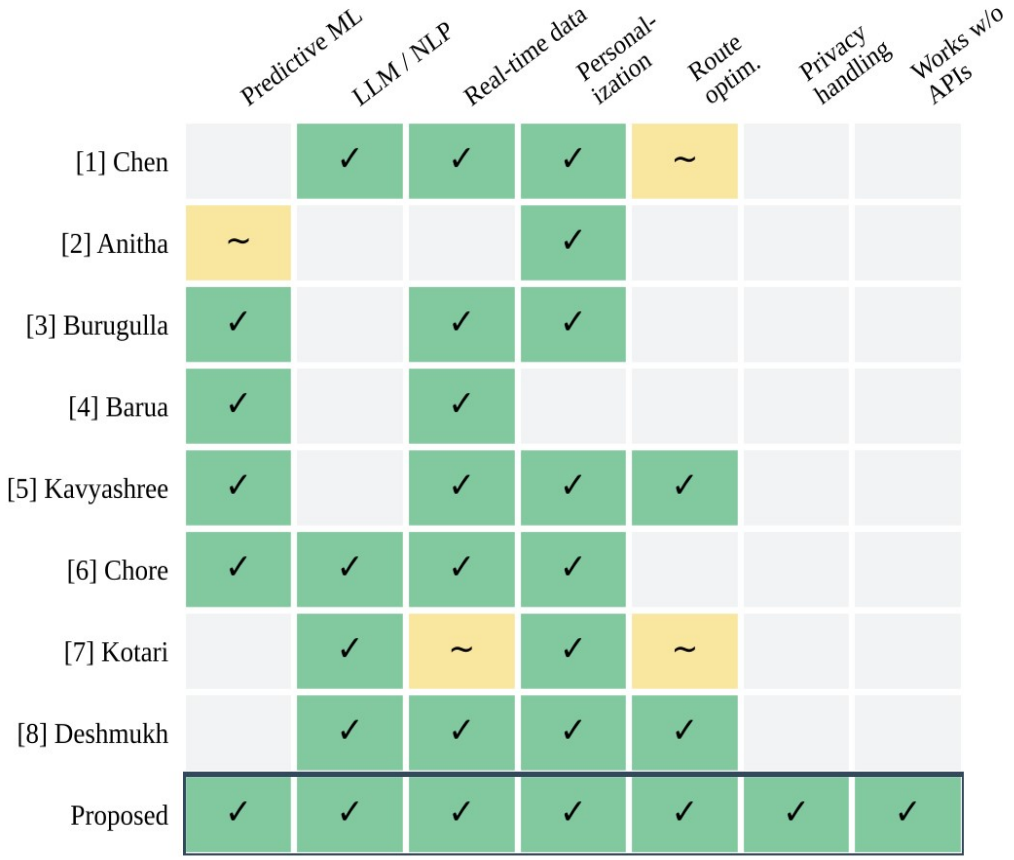


Fig. 6. Qualitative capability coverage of the reviewed studies and the proposed framework (✓ covered, ~ partial, blank not reported).

Most studies cover personalization and real-time data, and the LLM-based ones add natural-language planning [1], [6]–[8]. Predictive analytics is covered by [3], [4], [5]. None of the reviewed studies reports privacy handling or operation when an API fails; several list these as limitations instead. The distinguishing feature of the proposal is therefore the combination, not any single component.

Table V and Fig. 7 relate each research gap to the part of the framework intended to address it.

Table V: Research Gaps and Proposed Response

Gap	**Proposed response**
G1 Real-time data	Integration layer with validation and freshness checks
G2 Personalization	Profile built from history and feedback
G3 Third-party dependency	Caching and fallback sources

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G4 Decision intelligence	Weighted multi-criteria decision engine
G5 Privacy and security	Data minimisation, consent, secure storage
G6 Real-world validation	Pilot study with real users (Section IX)

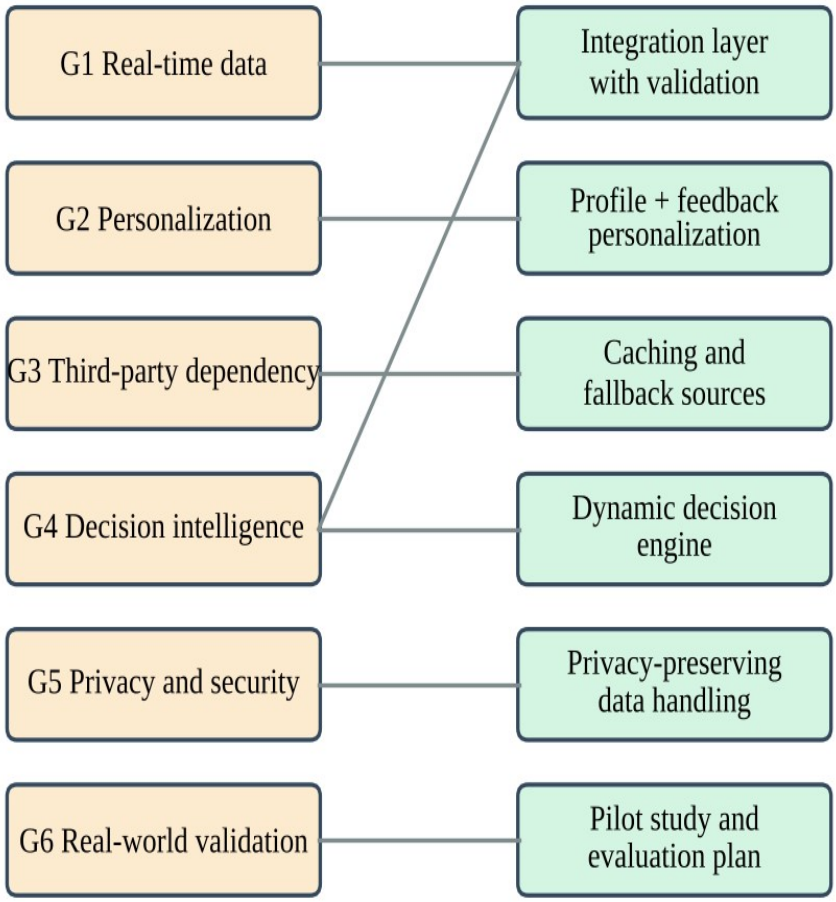


Fig. 7. Mapping of the six research gaps to the components of the proposed framework.

VIII. Ethical and Practical Considerations

A travel assistant manages confidential information such as an individual's residence, occupation, and travel schedules. The matter of privacy is analyzed in [3] and [6]. The system collects the necessary information only, gets storage approval from the client, and does not keep the data longer than needed. The help given should be suggestions, since it is the traveler who has the final say. The outcome obtained from LLM is sometimes wrong or outdated [6], [7], which is why the information about route and securing should not

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totally rely on the language model. Reasoning is important in this case because it helps to make UI see why a particular route has been given the first position. Another issue is fairness. A tool adjusted for average users can treat different audiences with a lower level of quality; accessibility issues can be encountered too.

The societal case for such a system is safer and more efficient travel, shorter delays, lower fuel use and better use of transport resources. These benefits are expected, not yet measured, and they should be checked in a real-world study.

IX. Evaluation Plan

Due to non-implementation of the system, the questions and measures that a future research study will need are illustrated in Table VI. Each measure must be compared with a standard measure, for instance, a navigation tool that helps find the shortest route. The results must be presented in a disaggregated way considering various aspects such as cities, time, and weather conditions rather than in an aggregated manner.

Table VI: Proposed Evaluation Plan

Question	Measure
Does it save travel time?	Travel time and delay vs. baseline
Are predictions accurate?	ETA and congestion forecast error
Are recommendations relevant?	User acceptance and ratings
Is it fast enough?	Response time per request
Does it survive API failure?	Quality with sources disabled
Is user data protected?	Privacy and security audit
Do users trust it?	Feedback on explanations

A pilot should engage genuine users for a number of weeks so that personalization can adjust (G2) and must involve phases where outside services are purposely restricted in order to examine the fallback design (G3). Combined, both suggestions tackle the issue of lack of proper validation (G6).

X. Limitations and Threats to Validity

This paper has three major shortcomings. To begin with, it is a literature-based review, meaning that no prototype is available to prove the positive effects of the proposed framework. The review considers only eight studies, which is sufficient to discover gaps but not to state that no other studies exist that deal with those gaps. Thirdly, the comparison of the systems' capabilities provided in Fig. 6 is qualitative and depends on how the author summarises each paper in Table I—other readers may assess some cells differently.

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Another drawback is that the investigated frameworks were developed for different locations, data sources, and technologies, which makes comparisons impossible.

XI. Conclusion and Future Work

This paper reviewed various studies on Travel Assistants based on AI technical advances. Predictive analytics, machine learning and language models combined with real-time data enhance travel planning and user experience, but the systems still depend on other companies' APIs as well as the quality of real-time data; moreover, limited personalization, too little attention to privacy issues and very few systems that have been validated in practice are the issues in the field. The authors propose a solution that fills these gaps, i.e. the system that includes integration layer, fallback methods, personalization, decision engine and explanatory and is presented as a design based on literature review. The plans for the future work based on the roadmap shown in Fig. 5 involve building data layer and models, introducing decision engine and explanatory interface and testing the system according to the measures presented in Table VI during a pilot project.

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