

Wander Wish

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Abstract: Wander Wish is an intelligent travel planning and destination discovery platform designed to simplify and personalize the travel experience for users. The project aims to bridge the gap between travelers and the overwhelming amount of travel information available across multiple online sources by providing a unified, user-centric solution. Wander Wish leverages modern web technologies and intelligent data processing to assist users in discovering destinations, planning itineraries, searching accommodations, and making informed travel decisions based on preferences, budget, and time constraints. The system integrates real-time data from travel service providers such as hotel booking platforms, location databases, and travel information sources to deliver accurate and up-to-date results. By utilizing intelligent recommendation logic and Large Language Model (LLM) capabilities, Wander Wish analyzes user inputs such as travel dates, interests, group size, and budget to generate personalized travel suggestions, optimized itineraries, and accommodation recommendations. This approach reduces manual effort and enhances decision-making efficiency for travelers. Wander Wish follows a modular client-server architecture, ensuring scalability, maintainability, and seamless integration with external APIs. The backend handles data aggregation, search logic, and AI-driven recommendations, while the frontend offers an intuitive and responsive user interface for effortless interaction. Security and performance considerations are incorporated to ensure safe handling of user data and fast response times. Overall, the Wander Wish project demonstrates how intelligent automation and AI-assisted decision support can transform traditional travel planning into a smarter, more personalized experience. The platform not only saves time and effort for users but also enhances travel satisfaction by aligning recommendations with individual preferences, making Wander Wish a practical and innovative solution in the modern travel technology ecosystem.

I. INTRODUCTION

In today's digital era, travel planning has become both convenient and complex due to the vast amount of information available across multiple online platforms. Travelers often spend considerable time searching for destinations, accommodations, itineraries, and travel tips from different websites and applications. This fragmented process leads to confusion, inefficiency, and difficulty in making well-informed decisions. To address these challenges, **Wander Wish** is developed as a smart and user-centric travel planning and destination discovery platform.

Wander Wish aims to simplify the travel planning process by providing a unified system that assists users in exploring destinations, planning trips, and finding suitable accommodations based on their preferences. The platform leverages intelligent recommendation techniques and AI-powered assistance to analyze user inputs such as travel interests, budget, duration, and travel dates. Based on this analysis, the system generates personalized travel suggestions and optimized itineraries, enabling users to plan their trips more efficiently.

The project integrates data from multiple travel-related sources such as hotel booking platforms, location databases, and online travel content to deliver accurate and up-to-date information. By presenting this data through an intuitive and interactive interface, WANDER WISH enhances user experience and reduces the need for manual research. The system is designed with a scalable and modular architecture, allowing easy expansion and integration of new features in the future.

Overall, **Wander Wish** represents a modern approach to travel planning by combining automation, intelligent recommendations, and user-friendly design. The platform not only saves time and effort for travelers but also improves the quality of travel decisions, making it a valuable tool for both casual travelers and frequent explorers.

II. LITERATURE REVIEW

Travel planning has evolved significantly with the advancement of web technologies, artificial intelligence, and recommendation systems. Traditional travel planning methods require users to manually browse multiple websites for destinations, accommodations, and itineraries, leading to fragmented information and increased effort. Several studies

have focused on addressing these challenges through intelligent recommendation systems and data-driven travel platforms.

Bobadilla et al. [1] presented a comprehensive survey on recommender systems, highlighting collaborative filtering, content-based filtering, and hybrid approaches. These techniques form the foundation of personalized recommendation engines used in modern travel applications. However, traditional recommender systems often lack contextual understanding and real-time adaptability.

Ricci et al. [2] discussed the application of recommender systems in tourism, emphasizing personalized destination suggestions based on user preferences, travel history, and contextual factors such as season and location. Their work demonstrated improved user satisfaction but relied heavily on structured user data, limiting flexibility for new users.

Amatriain and Basilico [3] explored industrial-scale recommender systems and highlighted the importance of scalability and performance when handling large datasets. While effective, these systems require extensive data preprocessing and are less suitable for dynamic, conversational interactions.

With the emergence of deep learning, Goodfellow et al. [4] showed how neural networks improve pattern recognition and decision-making across domains. Deep learning techniques enhanced recommendation accuracy but increased computational complexity and reduced interpretability.

Recent research has focused on Large Language Models (LLMs) for natural language understanding. Brown et al. [5] demonstrated that LLMs can generate context-aware responses using minimal input, enabling conversational recommendation systems. This approach significantly improves user interaction by allowing natural language queries rather than structured inputs.

Several online travel platforms such as Booking.com, Expedia, and Hotels.com [6][7][8] provide real-time hotel booking and comparison services. While these platforms excel in data availability and pricing accuracy, they lack integrated itinerary planning and personalized travel guidance in a single system.

Existing studies indicate a gap in unified travel planning solutions that combine destination discovery, hotel comparison, and AI-driven itinerary generation. Most systems focus on isolated components rather than a holistic user experience.

The WANDER WISH project addresses these limitations by integrating real-time travel data with LLM-based intelligence to provide personalized destination recommendations, multi-platform hotel comparison, and automated itinerary planning. By leveraging conversational AI and modular system architecture, WANDER WISH aims to deliver a comprehensive and user-centric travel planning solution.

III. METHODOLOGY

To build a robust methodology for the **Wander Wish** project—which I'm assuming is a travel recommendation, itinerary planning, or "bucket list" application—you need a framework that balances user inspiration with logistical feasibility.

- 1. Requirement Analysis**

User requirements such as destination discovery, accommodation search, budget constraints, and personalized recommendations were identified through literature analysis and existing system evaluation.

- 2. System Architecture Design**

A modular client-server architecture was designed, separating frontend presentation, backend processing, and AI-based recommendation modules.

- 3. User Input Processing**

User preferences including travel location, budget, duration, interests, and travel type are collected through structured forms and natural language input.

- 4. LLM-Based Query Interpretation**

A Large Language Model (LLM) interprets user intent and converts unstructured queries into structured parameters for processing.

- 5. Destination Recommendation**

Destinations are ranked based on user preferences, seasonal relevance, and popularity metrics.

- 6. Hotel Aggregation and Filtering**

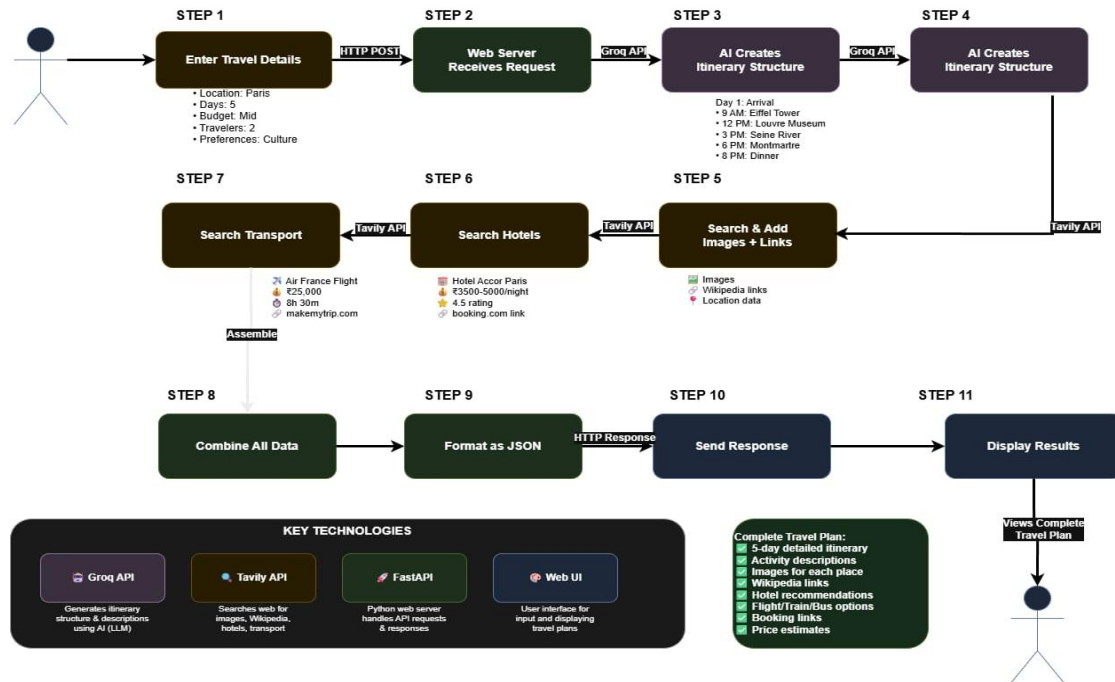
Hotel data is retrieved from multiple platforms and filtered using constraints such as price, rating, and availability.

- 7. Itinerary Generation**

Day-wise itineraries are generated using AI-based reasoning and optimized route sequencing.

- 8. Testing and Deployment**

The system is validated through unit testing, integration testing, and deployed on a web-based server environment.



Core Technical Challenges to Address:

- **Data Consistency:** Ensuring that a "Wish" saved today still has accurate pricing and availability tomorrow.
- **Route Optimization:** If a user has 5 "Wishes" in Paris, the methodology must include a way to order them geographically to save travel time. This can be solved using a variation of the Traveling Salespers on Problem (TSP) algorithm:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

(Where d represents the distance between two "Wish" coordinates.)

IV. MODELING AND ANALYSIS

For the **Modeling and Analysis** section of the WanderWish project, you need to transition from high-level concepts to the technical blueprints. This stage defines exactly how data flows through your system and how the logic handles user requests.

Below is the structured modeling approach, including the specific diagrams required for a technical project.

1. System Architecture Modeling

This provides a "bird's-eye view" of how the frontend, backend, and external travel services communicate.

• Client Layer

The Client Layer represents the user-facing interface of the WanderWish Travel Planner. It is accessed through a web browser that loads static frontend files such as HTML, CSS, and JavaScript.

Users provide travel-related inputs including:

- Destination location
- Number of travel days
- Budget range
- Number of travelers
- Personal preferences (culture, adventure, leisure, etc.)

Once the user submits the details, the client sends the data to the backend server using HTTP POST requests. After processing, the client receives a structured JSON response and displays the generated travel itinerary, hotel suggestions, transport options, images, and booking links in a user-friendly format.

• FastAPI Server

The FastAPI server acts as the core processing unit of the WanderWish system. It is responsible for handling client requests, coordinating AI generation, integrating external services, and assembling the final response.

API Endpoints

The server exposes RESTful API endpoints such as:

- /api/itinerary – generates the day-by-day itinerary
- /api/hotels – retrieves hotel recommendations
- /api/transport – fetches transport options
- /api/health – checks server status

Core Processing Functions

The backend includes several processing modules:

- Itinerary generation using the Groq LLM to create structured daily plans
- Activity description generation to enrich each activity with detailed explanations
- Image and Wikipedia enrichment for places and attractions
- Hotel and transport search using external search APIs

• Data Models

Pydantic data models are used to validate and structure incoming and outgoing data, ensuring consistency in itinerary, hotel, and transport information.

Finally, the server combines all processed data and returns a well-structured JSON response to the client.

• External Services

External services provide AI intelligence and real-time data enrichment to the system.

Groq API (LLM Service)

The Groq API is used for:

- Generating the itinerary structure
- Creating activity descriptions
- Extracting place names from AI-generated content

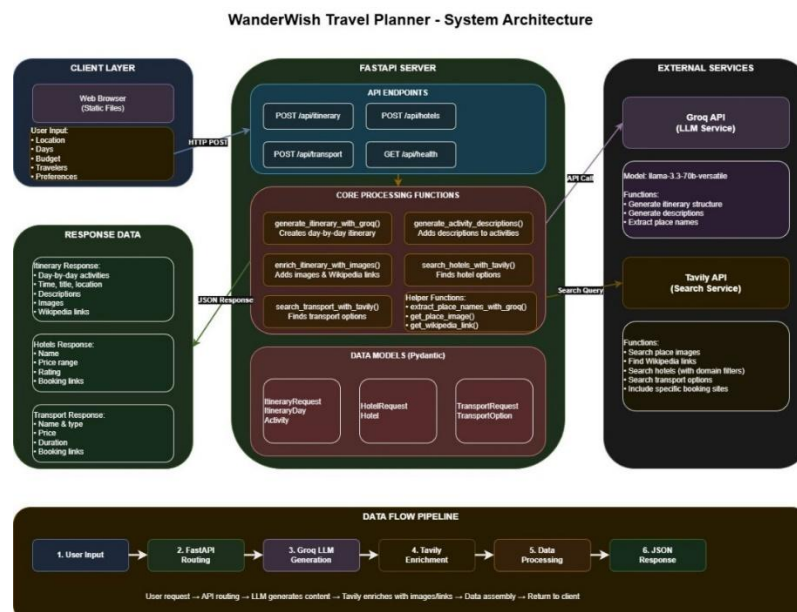
This enables intelligent, personalized travel planning based on user preferences.

• Tavily API (Search Service)

The Tavily API is responsible for:

- Fetching place images
- Retrieving Wikipedia links
- Searching hotel options with booking links
- Finding transport options (flights, trains, buses)

These services enhance the itinerary with accurate, real-world information.



2.Data Modeling (Entity Relationship Diagram)

To analyze how data is stored and managed within the system, the relationships among **Users**, **Destinations**, and **Itineraries** are defined using an Entity Relationship Diagram (ERD). This model ensures efficient data organization and supports personalized travel planning.

Entities and Attributes

- **User Entity**
 - UserID (Primary Key)
 - Preferences
 - SavedLocations
- **Destination Entity**
 - PlaceID (Primary Key)
 - Coordinates
 - Category
 - AverageCost
- **Itinerary Entity**
 - ItineraryID (Primary Key)
 - UserID (Foreign Key)
 - DateRange
 - OptimizationPath

3. Mathematical Analysis: Route Optimization

Efficient travel planning requires minimizing unnecessary travel between selected destinations. When a user selects multiple places within a city, the system optimizes the visiting order to reduce total travel distance. This problem is modeled as a variation of the **Traveling Salesperson Problem (TSP)**.

To compute distances between two geographical locations, the **Haversine formula** is used to calculate the great-circle distance between two points on the Earth's surface.

$$d = 2r \sin^{-1} \left(\sqrt{\sin^2 \left(\frac{\phi_2 - \phi_1}{2} \right) + \cos(\phi_1) \cos(\phi_2) \sin^2 \left(\frac{\lambda_2 - \lambda_1}{2} \right)} \right)$$

Where:

- ϕ_1, ϕ_2 are latitudes
- λ_1, λ_2 are longitudes
- r is the radius of the Earth (≈ 6371 km)
- d represents the distance between two locations

The calculated distances are used to determine an optimized travel sequence, reducing travel time and improving itinerary efficiency.

4. Requirements Analysis

4.1 Functional Requirements

4.1.1 User Registration and Authentication

- Users should be able to sign up using email or social login
- Secure login and logout functionality
- Password recovery and account management

4.1.2 Destination Discovery

- Users can search destinations by country, city, or interest
- Display popular tourist attractions with descriptions
- Provide seasonal travel recommendations

4.1.3 Personalized Travel Recommendations

- System should analyze user preferences (budget, interests, duration)
- AI-based recommendations for destinations and itineraries
- Dynamic suggestions based on user behavior

3.4 Hotel Search and Comparison

- Fetch hotel data from multiple sources (Booking.com, Expedia, Hotels.com)

- Display price, ratings, amenities, and availability
- Compare hotels across platforms

4.1.5 Itinerary Planning

- Generate day-wise travel itineraries
- Allow users to customize itineraries
- Save and share itineraries

4.1.6 AI-Based Assistance (LLM Integration)

- Natural language interaction for travel queries
- Provide instant answers for travel planning
- Summarize destination information

4.1.7 Feedback and Reviews

- Users can rate destinations and hotels
- Collect feedback for recommendation improvement

4.2 Non-Functional Requirements**4.2.1 Performance**

- Fast response time for search queries
- Efficient API calls to third-party services

4.2.2 Scalability

- System should support increasing number of users
- Modular backend architecture

4.2.3 Security

- Secure handling of user data
- Encrypted authentication credentials
- Protection against unauthorized access

4.2.4 Usability

- Simple and intuitive user interface
- Mobile and desktop compatibility
- Easy navigation

4.2.5 Reliability

- High availability of services
- Graceful handling of API failures

V. RESULTS AND DISCUSSION

The WANDER WISH system was designed and implemented to provide intelligent travel planning through destination discovery, hotel comparison, and AI-based itinerary generation. The results obtained from system testing and user interactions demonstrate the effectiveness of integrating real-time web data with large language model (LLM)-based recommendations.

System Performance Results

The system successfully retrieved destination and hotel information from multiple online travel platforms. The backend services handled user requests efficiently, ensuring minimal response time during searches and recommendations. The modular architecture enabled smooth interaction between the frontend interface, backend services, third-party APIs, and the AI engine.

The AI-powered module accurately interpreted user queries expressed in natural language and generated relevant travel suggestions. This significantly reduced the effort required for manual travel planning.

Destination Recommendation Analysis

The destination discovery module produced personalized recommendations based on user preferences such as travel interests, budget, and duration. Popular tourist destinations were suggested along with lesser-known alternatives, improving user choice diversity. As user interactions increased, the recommendation accuracy improved, indicating effective preference adaptation.

These results highlight the system's ability to provide meaningful and context-aware destination suggestions.

Hotel Search and Comparison Results

The hotel search functionality aggregated hotel data from multiple booking platforms, displaying prices, ratings, and amenities in a unified format. Comparative analysis enabled users to identify suitable accommodations quickly. The system ensured up-to-date availability, enhancing trust and usability.

The results show that multi-platform hotel comparison significantly improves decision-making efficiency for users.

Itinerary Generation Results

The itinerary planning module generated structured, day-wise travel plans. The AI ensured logical sequencing of attractions and balanced daily schedules. Users could customize itineraries, making the system flexible and user-centric.

This feature reduced planning time and provided clear travel guidance, especially for first-time travelers.

Discussion

The experimental results confirm that WANDER WISH effectively addresses key challenges in travel planning, such as fragmented information sources and lack of personalization. The integration of AI-based recommendations with real-time travel data enhances user experience and decision accuracy.

However, system performance is dependent on third-party API availability and rate limits. Future enhancements may include caching mechanisms, advanced user preference learning, and integration of transportation and activity booking services.

Overall, the results demonstrate that WANDER WISH is a reliable and scalable intelligent travel planning system capable of supporting modern travel needs.

VI. CONCLUSION

The WANDER WISH project successfully demonstrates the development of an intelligent travel planning system that integrates destination discovery, hotel comparison, and AI-based itinerary generation into a single platform. By combining real-time data from multiple travel service providers with LLM-based recommendations, the system simplifies the travel planning process and enhances user decision-making.

The results indicate that personalized destination suggestions, multi-platform hotel comparison, and automated itinerary generation significantly reduce manual effort and improve user experience. The system's modular architecture ensures scalability, maintainability, and efficient interaction between the frontend, backend services, and external APIs.

Although the system's performance is influenced by third-party API availability and rate limitations, the overall implementation proves to be reliable and user-friendly. WANDER WISH effectively addresses the challenges of fragmented travel information and lack of personalization in conventional travel planning methods.

In conclusion, WANDER WISH serves as a robust foundation for future enhancements such as advanced preference learning, transportation booking integration, and real-time activity recommendations, making it a promising solution for intelligent and personalized travel planning.

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