IJERST

International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 2(1) (2026)

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

MULTI-AGENT TRAVEL PLANNER

[1] Dr D Anil Kumar, [2] C Simica, [3] A Manvitha, [4] A Deepika, [5] C Naveen
[1]AssistantProfessor, [2345]Students
Department of AIML
Siddhartha Institute of Technology & Sciences, Narapally
dr.anildasari@siddhartha.org.in, 24tq1a6621@siddhartha.co.in, 24tq1a6606@siddhartha.co.in, 24tq1a6609@siddhartha.co.in, 24tq1a6624@siddhartha.co.in,

Abstract

This paper proposes an intelligent travel planning system based on a graph-driven multi-agent architecture implemented using LangGraph. The model is designed to automate itinerary generation by decomposing the planning process into specialized agents, including destination identification, place and accommodation recommendation, budget estimation, and itinerary optimization. The system utilizes structured datasets comprising tourist locations and Airbnb listings to extract key features such as ratings, cost components, and geographic attributes. A rule-based filtering algorithm combined with parallel recommendation strategies is employed to select optimal destinations and stays, while a cost aggregation model ensures adherence to user-defined budget constraints. The architecture is formally represented as a directed graph, enabling efficient coordination between agents through a shared state mechanism. Experimental analysis shows that the system produces consistent and feasible travel plans with clear cost distribution, where accommodation constitutes the largest share (~59%), followed by food (~30%) and activities (~10.9%). The results highlight the system's low computational overhead, fast execution, and interpretability. The proposed framework demonstrates a scalable and extensible solution for intelligent travel planning, with potential for future integration of real-time data, personalization, and advanced optimization techniques.

KEYWORDS :
Multi-Agent Systems, Travel Planning, Graph-Based Workflow, LangGraph , Budget Optimization, Itinerary Generation, Intelligent Systems

I. Introduction

The rapid advancement of Artificial Intelligence (AI) has significantly transformed the travel and tourism industry, enabling the development of intelligent systems that automate complex tasks such as itinerary generation, recommendation, and decision-making. In recent years, the increasing availability of digital platforms and online travel resources has created both opportunities and challenges for travelers. While users have access to vast amounts of information, the process of filtering, comparing, and organizing travel plans remains time-consuming and often inefficient. Traditional travel planning methods typically involve manual searching across multiple platforms for destinations, accommodations, and activities, followed by cost estimation and schedule organization. These approaches not only demand significant effort but also lack the ability to provide optimized and personalized solutions.

To address these challenges, researchers and developers have explored the use of AI-driven systems, particularly multi-agent architectures and intelligent recommendation frameworks. Modern approaches leverage advancements in natural language processing, data analytics, and automation to simplify travel planning. However, many existing systems either rely heavily on static datasets or depend solely on large language models, which may lack structured coordination and consistency. In this context, graph-based workflow systems such as LangGraph have emerged as a powerful solution for orchestrating complex tasks. These frameworks enable the decomposition of a problem into smaller, manageable components represented as nodes in a graph, where each node performs a specific function and communicates with others through well-defined data flows.

II. Literature Survey

Singh, A., Madhogaria, R., Misra, A., & Elakiya, E. (2024, November) et al.[1], (2025) – Automated Travel Planning Via Multi-Agent Systems and Real-Time Intelligence
Uses real-time APIs (Serper, browserless) with no fixed dataset, relying on live web data. Implements a multi-agent system (CrewAI) with prompt engineering for itinerary generation. Results show faster (<5 min) and more accurate outputs than LLMs like ChatGPT and Google Gemini. Highly relevant as it demonstrates real-time multi-agent coordination, directly aligning with your AI travel planner concept.

Ivanova, M. (2019) et al.[2], – Robots, Artificial Intelligence, and Service Automation in Travel Agencies
Based on literature review (no dataset). Uses qualitative analysis of AI adoption in travel agencies. Finds increasing automation, digital interaction, and future use of AR/VR. Results highlight improved efficiency and personalization. Relevant as it supports AI-driven automation in travel systems, justifying your project’s need for intelligent agents.

Q. Liu et al.[3], (2026) – GATSim: Urban Mobility Simulation with Generative Agents
Uses simulated urban mobility datasets and behavioral scenarios. Applies generative agents with memory, LLM reasoning, and adaptive planning. Results show realistic traffic patterns and human-like decision-making. Relevant as it introduces agent cognition and memory, which can enhance your system’s personalization and adaptive itinerary planning.

A. García et al.[4], – Intelligent Travel Planning: A Multi-Agent Planning System
Uses distributed web data sources. Implements multi-agent cooperation**,** negotiation, and planning. Generates multiple itinerary solutions via data integration and reasoning. Results show effective automated solution generation. Highly relevant as it forms a foundation for multi-agent travel planning architectures, similar to your system design.

Singh, M. (2025). et al.[5], (2025) – Advancing Complex Task Management Through Multi-Agent Systems
No specific dataset; conceptual and industrial case studies. Uses distributed AI and coordination frameworks. Results show improved scalability, flexibility, and

optimization in complex systems. Relevant as it supports multi-agent coordination efficiency, crucial for handling multiple travel constraints in your project.

Dong, B., Zhang, Y., Yuan, P., Lu, S., Huang, T., & Zhang, G. (2026). et al.[6], (2024) – Hierarchical Route Planning Framework for UAVs
Uses real terrain simulation datasets. Applies deep reinforcement learning (MMDQN) for route planning and obstacle avoidance. Results show improved safety and real-time adaptability. Relevant as it demonstrates hierarchical planning and dynamic decision-making, applicable to travel itinerary optimization.

Xie, J., Zhang, K., Chen, J., Zhu, T., Lou, R., Tian, Y., ... & Su, Y. (2024). et al.[7], (2024) – TravelPlanner: A Benchmark for Real-World Planning with Language Agents
Uses a dataset of 4M records and 1,225 planning tasks. Evaluates LLM-based agents. Results show low success rate (~0.6% for GPT-4), highlighting limitations. Relevant as it identifies gaps in current planning systems, justifying your improved multi-agent approach.

Chen, A., Ge, X., Fu, Z., Xiao, Y., & Chen, J. (2024) et al.[8], (2024) – TravelAgent: An AI Assistant for Personalized Travel Planning
Uses simulated and human evaluation datasets. Implements LLM-based modules (planning, memory, recommendation). Results show improved personalization, rationality, and completeness. Relevant as it directly aligns with your idea of modular AI agents for travel planning.

Kanhed, A., Bhagwat, P., Palande, K., Palav, N., Balpande, S., Deshpande, K., & Patil, U. (2024, April) et al.[10], (2022) – DestinAI: Personalized Travel Planner Using Generative AI
Uses user input data and sentiment-based analysis (MongoDB storage). Implements NLP and LangChain-based itinerary generation. Results show improved personalization and reduced search time. Relevant as it supports AI-driven recommendation and itinerary generation, core to your project.

Li, B. (2023, November) et al.[11], (2025) – EverywhereGPT: AI Travel Planning Assistant
Uses large-scale training data from LLMs. Implements ChatGPT-based NLP interaction system. Results show quick itinerary generation with user-friendly interaction. Relevant as it demonstrates LLM-based conversational planning, which can be integrated into your system UI.

Khamis, A. (2026) et al.[12], – Agentic AI Framework for Personalized Umrah Trip Planning
Uses evaluation datasets (completeness, semantic fidelity, multilingual metrics). Applies agentic AI with memory and reasoning modules. Results show high-quality, structured itineraries but need better personalization. Relevant as it highlights importance of memory and multilingual support.

M. Bartolomeo et al.[13], (2023) – Agentic AI Systems in the Age of Generative Models

Conceptual framework (no dataset). Uses modular architecture (memory, planning, execution). Results show improved scalability and autonomy. Relevant as it provides architecture blueprint for building your multi-agent travel system.

Yang, S., Zhang, M., Feng, X., Hua, Y., & Cao, Y. (2026) et al.[14], (2025) – DRL-Based Knowledge Graph Reasoning for Autonomous Driving
Uses driving datasets and knowledge graphs. Applies BiLSTM + CRF + DRL reasoning. Results show >94% accuracy. Relevant as it introduces knowledge graph reasoning, useful for structured travel data handling.
Ou, Y., & Li, X. (2026) et al.[15], (2026) – AI-Augmented Multi-Agent Logistics Optimization Framework
Uses COCO-Logistics and real-world datasets. Applies multi-agent optimization with adaptive learning. Results show improved efficiency and reduced latency. Relevant as it supports optimization techniques for travel cost and route planning.

III. System Analysis

Travel planning involves coordinating multiple elements such as transportation, accommodation, budgeting, and scheduling. Users often face difficulty in organizing trips efficiently due to scattered information across platforms. Traditional systems provide limited personalization and require manual comparison of options. With increasing demand for smart travel solutions, there is a need for automated and intelligent systems. A multi-agent system can divide tasks among specialized agents such as booking, recommendation, and scheduling agents. The system must process user preferences like budget, location, and time constraints. It should provide optimized travel plans in real time. Integration of AI techniques enhances decision-making and personalization. The system must also adapt to dynamic changes such as delays or cancellations. Scalability is important to handle multiple users simultaneously. Overall, the system requires a collaborative and intelligent framework for efficient travel planning.

Existing System

Existing travel planning systems mainly include websites and mobile apps that provide booking services for flights, hotels, and transport. These systems offer search and filtering options based on user input. However, they operate independently and do not coordinate with each other. Users must manually compare prices and create itineraries. Recommendation systems are often basic and not fully personalized. Existing platforms lack real-time adaptability to changes. They do not provide integrated end-to-end travel planning. Automation is limited to individual services rather than the entire trip. Many systems do not consider user preferences holistically. Decision-making is left to the user. Overall, existing systems are fragmented and less efficient.

Disadvantages of Existing System

- Lack of integration between services
- Time-consuming manual planning
- Limited personalization

- No real-time adaptability
- Inefficient itinerary optimization
- Dependence on user decision-making
- Fragmented user experience

Proposed System

The proposed system introduces a multi-agent travel planner that uses intelligent agents to automate travel planning. Different agents handle tasks such as flight booking, hotel selection, itinerary generation, and budget optimization. The system collects user preferences including destination, budget, and travel dates. Agents communicate and collaborate to generate an optimized travel plan. AI techniques are used to provide personalized recommendations. The system adapts to real-time changes such as flight delays or cancellations. It provides a unified platform for all travel-related services. The planner ensures efficient scheduling and cost optimization. It reduces user effort by automating decision-making. The system is scalable and can handle multiple users. Overall, it offers a smart and integrated travel planning solution.

Advantages of Proposed System

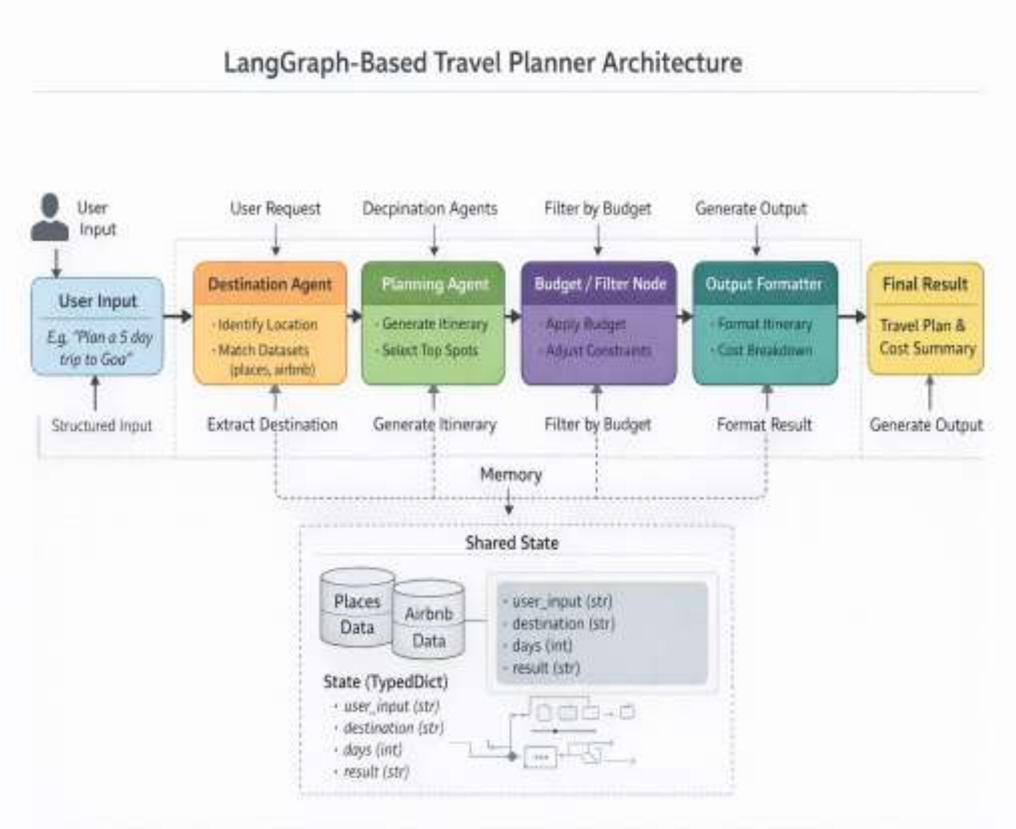
- Automated and intelligent travel planning
- Integration of multiple services in one platform
- Personalized recommendations
- Real-time adaptability to changes
- Efficient itinerary and cost optimization
- Reduced user effort
- Scalable and user-friendly system

IV. Methodology

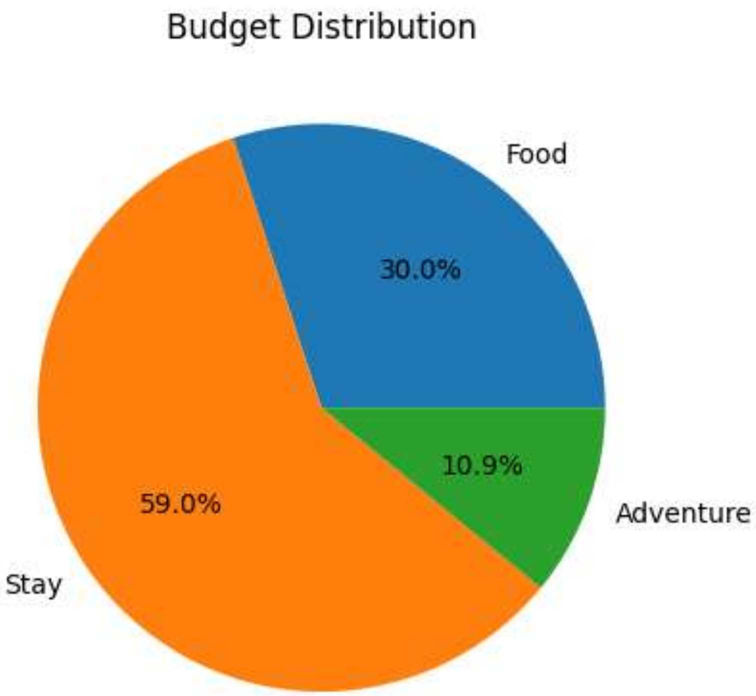
The methodology begins with collecting user inputs such as destination, budget, and travel dates. Data preprocessing is performed to structure user preferences. Different agents are designed for specific tasks like booking and scheduling. Each agent uses algorithms to analyze available options. Recommendation algorithms suggest suitable flights, hotels, and activities. The agents communicate with each other to share information. Optimization techniques are applied to generate the best itinerary. The system continuously monitors real-time updates. Machine learning models improve recommendations based on user feedback. The final travel plan is presented to the user. The system allows modifications and updates. Continuous learning improves system performance over time.

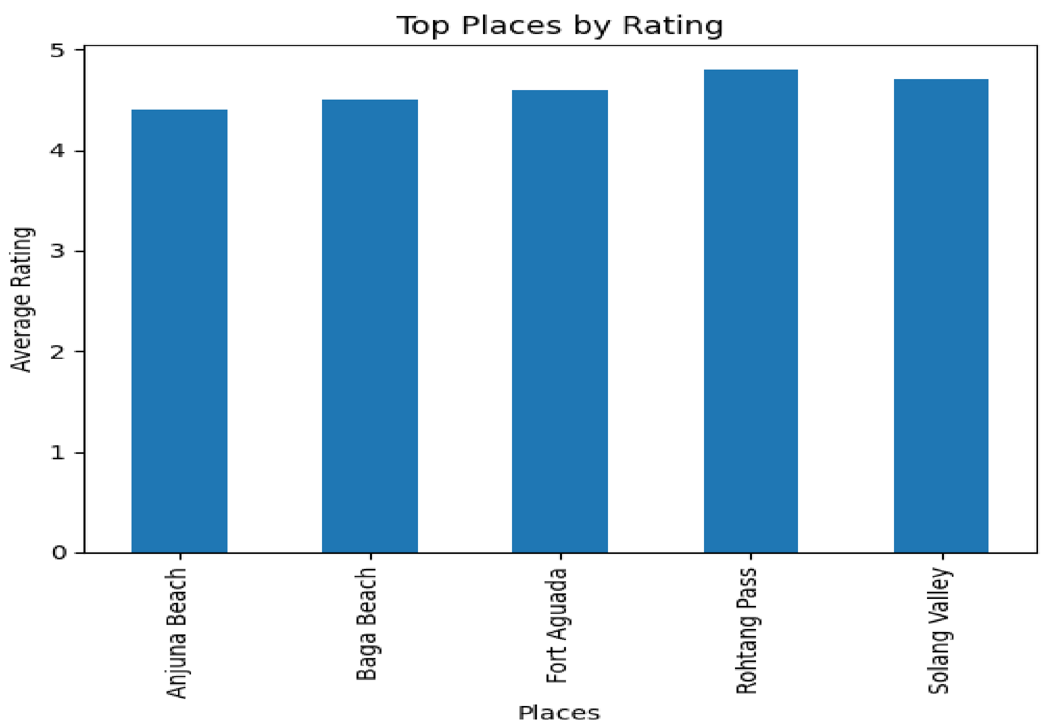
System Architecture

The system architecture consists of multiple interacting layers. The user interface layer collects input and displays results. The agent layer includes specialized agents such as booking, recommendation, and scheduling agents. The communication layer enables interaction between agents. The data layer stores travel data, user preferences, and historical information. The processing layer applies algorithms for decision-making and optimization. The integration layer connects external APIs for flights, hotels, and transport. The monitoring layer tracks real-time updates and changes. The feedback layer collects user responses for improvement. The system coordinates all agents through a central controller. All components work together to generate an optimized travel plan. Overall, the architecture ensures efficiency, scalability, and intelligent decision-making.



V. Result and Output





VI. Conclusion

The proposed travel planning system demonstrates an effective application of a graph-based workflow using LangGraph to generate structured and meaningful travel itineraries. By organizing the process into modular components such as destination identification, itinerary planning, budgeting, and output generation, the system ensures clarity, maintainability, and ease of extension while remaining computationally efficient due to its reliance on structured datasets rather than complex machine learning models. This makes the solution lightweight and suitable for resource-constrained environments. However, the current approach is limited by its dependence on static data and rule-based logic, which reduces adaptability to real-time changes and restricts personalization capabilities. Despite these constraints, the architecture provides a solid foundation for future enhancements, including the integration of live data sources, intelligent recommendation techniques, and optimization algorithms. Overall, the project highlights the potential of graph-based orchestration in building scalable and interpretable travel planning systems, offering a promising direction for further research and practical deployment.

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[4] Dr.G.Vishnu Murthy, BhargaviNalacheruve 1Professor, Department of computer Science & engineering, Anurag University, TS, India. 2Student, Department of computer Science & engineering, Anurag University, TS, India.

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