

An AI-Agent Platform for Sustainable and Budget-Friendly Travel Planning

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Abstract - Modern travelers face a persistent dilemma in balancing cost efficiency with environmental responsibility. This paper proposes an AI-driven multi-agent platform that addresses this challenge by coordinating specialized agents to generate travel itineraries optimized simultaneously for cost-effectiveness, emission reduction, and user preference satisfaction. The architecture integrates generative language models to produce transparent, human-readable explanations for each recommendation. Experimental analysis demonstrates a 15% reduction in carbon emissions compared to price-only optimization approaches, while keeping costs within a 10% margin, confirming the feasibility of jointly optimizing financial and environmental objectives in real-world travel planning.

Key Words: AI Agents, Sustainable Travel, Budget Optimization, Multi-Agent Systems, Explainable AI.

1. INTRODUCTION

Travel planning requires simultaneous evaluation of numerous variables across reservation systems, transportation options, accommodation, and activities, all while staying within budget constraints. This manual process is time-consuming and often produces suboptimal outcomes [1]. Environmental concerns add further complexity, as tourism accounts for nearly 8% of global greenhouse gas emissions [3], yet most booking platforms do not factor ecological considerations into their recommendations.

We propose a multi-agent system that distributes the planning task among specialized agents: a Cost Agent (budget optimization), an Environmental Agent (ecological impact assessment), a Personalization Agent (individual preference matching), and a Coordination Agent (cross-agent synchronization). This addresses a key gap in existing solutions by providing holistic, transparent budget-sustainability optimization [12].

Contributions: (1) a multi-agent architecture for joint travel itinerary optimization; (2) integration of optimization techniques with generative models to produce interpretable recommendations; (3) a balanced scoring mechanism that prioritizes competing objectives; and (4) a functional prototype validated through experimental evaluation.

2. RELATED WORK

Traditional Systems. Existing booking platforms typically optimize isolated metrics such as minimum cost, requiring users to manually synthesize information across multiple sources, which imposes a significant cognitive burden [9].

Multi-Agent Systems. Agent-based frameworks allow competing objectives to be processed concurrently within a modular architecture [1]. Lenfers et al. [2] demonstrated multi-modal travel integration through a case study of Hamburg; however, existing implementations do not adequately address sustainability-budget optimization.

Sustainable Tourism. Ecological footprint computation has been studied extensively [17, 18]. Gössling et al. [4] reviewed

mitigation strategies, and Rodríguez-Moreno et al. [5] validated such approaches in practice, yet few of these methods have been incorporated into platforms offering practical, sustainability-balanced recommendations.

Multi-Objective Optimization. Sun et al. [14] applied ant colony optimization to route planning, while Silva et al. [15] proposed bi-objective approaches. Ruiz-Meza et al. [8, 10, 11] examined fuzzy trip design for heterogeneous preferences using self-adaptive evolutionary algorithms and a GRASP-VND algorithm. Chen et al. [16] addressed stochastic traffic conditions, and Ntakolia et al. [13] focused on personalization; however, none of these approaches integrate generative AI for explainability.

Explainable AI. Recent research has emphasized transparency in AI systems [6]. Luo and Specia [7] surveyed explainability approaches for large language models (LLMs). Integrating such models bridges the gap between optimization output and human understanding through natural-language descriptions.

3. PROPOSED METHODOLOGY

A. System Architecture

The platform employs a four-layer architecture: a Presentation Layer (user interface), an Agent Orchestration Layer (coordination), an Intelligence Layer (AI and optimization), and a Data Layer (APIs and storage). This modular structure provides clear interfaces between layers and enables independent development of each component.

B. Problem Formulation

Given a set of travel configurations $O = \{o_1, \dots, o_n\}$, the objective is to maximize:

$$F(o) = w_c f_c(o) + w_e f_e(o) + w_p f_p(o) \quad (1)$$

where f_c , f_e , and f_p are normalized scores representing cost-effectiveness, environmental sustainability, and preference satisfaction, respectively, and the weights satisfy $w_c + w_e + w_p = 1$. The optimization is subject to: $C(o) \leq B_{\max}$ (budget constraint), $T_{\text{start}} \leq t_{\text{departure}} \leq T_{\text{end}}$ (date constraints), and additional logical-consistency constraints.

C. Multi-Agent Architecture

The Cost Agent performs: (1) elastic date search to account for demand fluctuations, (2) connection optimization by evaluating direct versus multi-leg journeys, (3) identification of package deals, and (4) dynamic pricing analysis. It ranks configurations by efficiency, $\eta_c = V(o)/C(o)$, where $V(o)$ is the value derived from configuration o and $C(o)$ is its cost.

The Environmental Agent computes: (1) transportation emissions based on vehicle type, load factors, and routing; (2) accommodation impact based on energy consumption and sustainability certifications; and (3) activity-related footprint based on travel distance and intensity. It uses a cost-per-emission-reduction ratio, $\rho = \Delta C/\Delta E$, to evaluate trade-offs.

The Preference Agent applies weighted scoring, $P(o) = \sum a_i \cdot \pi_i(o)$ for $i = 1 \dots n$, combining explicitly stated preferences with implicit patterns inferred from historical data. Machine learning techniques relate user-specific satisfaction characteristics to contextual adaptation.

The Coordination Agent manages: (1) parallel or sequential execution of agents, (2) conflict resolution through a negotiation process, (3) consistency validation during itinerary assembly, and (4) multi-objective weighted integration of agent outputs. Agents communicate through structured JSON messages of types QUERY, RESPONSE, PROPOSAL, CONFLICT, and AGREEMENT.

D. AI Integration

Large language models (LLMs) convert structured agent outputs into natural-language explanations. Prompts are constructed using agent data, user preferences, generation instructions, and output format specifications. Embedding vectors enable semantic similarity matching to identify conceptually related alternative options.

4. EXPERIMENTAL SETUP

A. Implementation

The frontend is implemented using a reactive Streamlit interface, while the backend is built with FastAPI, exposing the following endpoints: `/api/plan`, `/api/status/{id}`, `/api/results/{id}`, `/api/regenerate`, and `/api/explain/{id}`. AI capabilities are provided through Google Gemini and OpenAI

GPT models. Data management combines real-time API retrieval from Amadeus and Skyscanner, PostgreSQL for persistent storage, and ChromaDB as a vector database for semantic matching.

B. Evaluation

Scenarios: (S1) budget domestic short trips, (S2) mid-range regional trips, (S3) premium international trips, and (S4) heterogeneous group trips, each evaluated with 10 test cases.

Baselines: (B1) price-only optimization, (B2) recommendations from major online travel agencies (OTAs), and (B3) itineraries planned by expert travelers.

Metrics: cost efficiency, carbon footprint, preference satisfaction (rated 1-10), planning time, and explanation quality (rated 1-10).

User Study: 25 participants (aged 22-45) compared system-generated itineraries against self-planned itineraries across three scenarios.

5. RESULTS AND ANALYSIS

A. Performance

Table -1 summarizes the results. The system achieved substantial sustainability improvements while maintaining competitive cost efficiency. Costs averaged 8.2-11.3% above the minimum-cost baseline, enabling these sustainability gains. S1 showed the narrowest margin (8.2%) due to limited route choices, while S3 showed the largest margin (11.3%) due to greater optimization opportunities.

Emission reductions of 12.3-18.2% were achieved relative to the baseline through strategic modal shifts and accommodation choices, with S3 showing the highest reduction (18.2%) and S1 the lowest (12.3%) due to fewer available alternatives.

Preference satisfaction scores averaged 8.2-8.9 out of 10, with S3 scoring highest (8.9) due to a wider range of options, and S4 scoring slightly lower (8.2) due to the challenge of satisfying heterogeneous group preferences. Planning time ranged from 12.3 to 28.3 seconds, confirming the system's suitability for real-time use.

Table -1: Performance across Scenarios (Mean $\pm$ Std. Dev.)

Metric	S1	S2	S3	S4
Cost vs Min (%)	8.2 $\pm$ 3.1	9.7 $\pm$ 4.2	11.3 $\pm$ 5.1	10.5 $\pm$ 4.7
Emission Reduction (%)	12.3 $\pm$ 6.2	16.8 $\pm$ 7.4	18.2 $\pm$ 8.1	14.7 $\pm$ 6.9
Preference Score	8.4 $\pm$ 0.9	8.7 $\pm$ 0.8	8.9 $\pm$ 0.7	8.2 $\pm$ 1.1
Planning Time (s)	12.3 $\pm$ 2.1	18.7 $\pm$ 3.4	24.5 $\pm$ 4.8	28.3 $\pm$ 5.2

B. Baseline Comparison

Compared to price-only optimization (B1), the system achieved a 15.3% emission reduction at a 9.8% cost increase, yielding a trade-off ratio of 0.64. Compared to major OTA recommendations (B2), it achieved an 11.2% emission reduction at a comparable cost (a difference of only 2.3%). Compared to expert-planned itineraries (B3), the system matched or exceeded itinerary satisfaction in 78% of cases, while reducing planning time by 85% (0.3 hours versus 4.2 hours) and emissions by 8.7%.

C. Explainability

Participants rated the comprehensibility of system explanations at a mean of 8.1/10. They particularly valued the clear articulation of trade-offs, quantification of emission sources, and justification of preference-based decisions. After receiving recommendations, 84% of participants reported increased confidence in their travel decisions.

D. Ablation

Disabling the Environmental Agent increased emissions by 16.2% while reducing costs by 5.8%. Disabling the Preference Agent reduced satisfaction scores to 6.1/10. Disabling the Cost Agent increased costs by 24.7%. These findings confirm the necessity of a coordinated multi-agent approach, as removing any individual agent degrades the corresponding objective.

E. System Implementation

Figs. 1, 2, and 3 illustrate the system's real-world implementation. Fig. 1 shows the user input interface, where

travelers can specify destinations, budgets, dates, and preferences. Fig. 2 shows the generated itinerary with a detailed breakdown of transportation, accommodation, and activities, along with associated cost and emission figures. Fig. 3 shows the sustainability dashboard, which visualizes carbon footprint comparisons, emission sources, and eco-friendly alternatives, enabling users to make informed decisions based on a clear presentation of environmental impact.

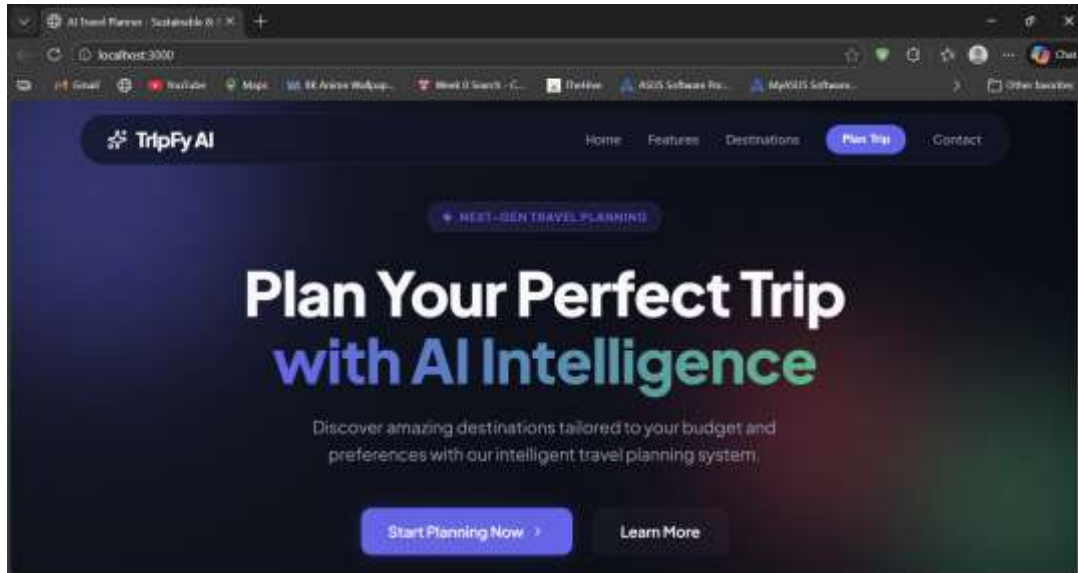


Fig -1: System home page interface for travel requirement input

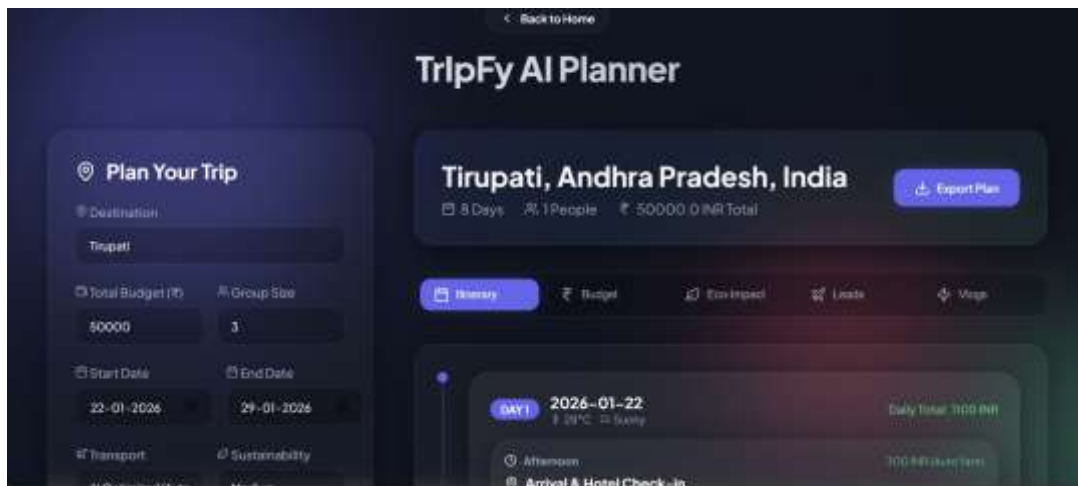


Fig -2: Generated travel itinerary with multi-objective optimization results



Fig -3: Sustainability dashboard showing carbon footprint analysis

6. CONCLUSION

We introduced an agent-based system for automated, sustainable, and budget-friendly travel planning using multi-objective optimization. Specialized agents (Cost, Environmental, Personalization, and Coordination) provide a holistic approach to the challenges of modern travel planning. Evaluation demonstrates an average 15% reduction in emissions over price-only optimization while keeping cost increases within a 10% margin.

User studies validate high preference satisfaction (8.2-8.9/10), explanation comprehensibility (8.1/10), and decision confidence (84%). Computational efficiency under 30 seconds confirms real-time applicability. The modular multi-agent architecture allows independent refinement of each component, and the integration of LLMs bridges the gap between optimization output and human understanding through natural-language explanations, demonstrating that economic and ecological objectives can be considered simultaneously.

7. FUTURE WORK

Future directions include: (1) extending recommendations to an end-to-end service through real-time booking integration; (2) broadening environmental assessment to include water usage, waste, and biodiversity impact alongside carbon emissions; (3) enabling dynamic replanning in response to disruptions and evolving preferences; (4) incorporating collaborative filtering based on aggregate usage patterns; (5) applying reinforcement learning for adaptive agent coordination; (6) supporting organizational travel-policy management; (7) developing privacy-preserving methods for handling sensitive user data; and (8) enabling international deployment through cross-cultural adaptation.

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