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Smart Travel Planner and Budget Manager: An AI-Assisted Itinerary and Expense Optimisation System

Prathamesh S. Bhosale[1], Anushka R. Nikam[2]
Department of Computer Science and Engineering
Institute of Engineering and Technology, Latur, Maharashtra, India

Abstract—Planning a multi-day trip conventionally requires a traveller to reconcile information scattered across destination guides, transport schedules, accommodation listings, and a self-maintained spreadsheet budget, with little automated support for keeping the itinerary and the budget consistent with each other. This paper presents the design, implementation, and evaluation of a Smart Travel Planner and Budget Manager: a web-based system that generates a day-wise itinerary from a small set of traveller preferences, estimates and tracks trip expenditure against a declared budget, and recommends itinerary or spending adjustments when a plan is projected to exceed its budget. The system integrates four components — a constraint-based itinerary generation engine that sequences points of interest under daily time and travel-distance limits, a cost estimation module that combines historical fare and tariff data with live currency conversion, a budget tracking module that compares planned versus actual expenditure across accommodation, transport, food, and activity categories, and a recommendation engine that proposes lower-cost substitutes when a category is projected to overrun. A dataset of 6,200 points of interest, fare records, and accommodation tariffs across eighteen Indian destinations was assembled to drive itinerary generation and cost estimation. The itinerary generator produced schedules that respected all stated daily time constraints in 97.3% of 500 generated trials, and the cost estimator achieved a mean absolute percentage error of 9.2% against actual recorded trip expenditure from a twenty-user field trial. Participants using the full system reported a 26% reduction in planning time and stayed within their declared budget in 80% of trips, compared with 45% for a control group using a conventional spreadsheet. The paper documents the system architecture, module design, evaluation methodology, observed limitations, and future scope of the work.

Index Terms—Travel Planning, Budget Management, Itinerary Generation, Constraint Satisfaction, Expense Tracking, Recommendation System, Route Optimization, Trip Cost Estimation, Tourism Technology, Decision Support System, Mobile and Web Application, Personalised Recommendation.

I. INTRODUCTION

Leisure and business travel generate a planning burden that is disproportionate to the length of the trip itself. A traveller must simultaneously decide which places to visit, in what order, on which day, while separately tracking how each decision affects an overall trip budget that spans accommodation, local transport, food, and activity spending. These two concerns — the itinerary and the budget — are almost always managed in separate tools, with no automated mechanism to flag when an attractive itinerary has quietly become unaffordable [1], [2].

Existing travel applications address parts of this problem in isolation. Itinerary planners recommend points of interest and generate day plans but rarely incorporate a hard budget constraint into the sequencing decision. Expense trackers record spending after it occurs but provide no forward-looking estimate of what a planned itinerary will cost before the trip begins. The result is that travellers routinely discover budget overruns only after committing to bookings that are difficult to reverse [3].

B. Data Layer

The data layer maintains a curated database of points of interest, transport fare records, and accommodation tariffs for each supported destination, together with average visit duration and typical activity cost per point of interest. Records are refreshed periodically from public tourism datasets and partner listings.

C. Preference Intake Module

The traveller supplies a small set of preferences: destination, trip duration, total budget, preferred pace, and interest categories such as heritage, nature, food, or adventure. These preferences are converted into scoring weights used by the itinerary generator to rank candidate points of interest.

D. Itinerary Generation Engine

The itinerary engine constructs a day-wise schedule using a greedy nearest-neighbour heuristic seeded by preference score, subject to a per-day time budget and a maximum inter-stop travel distance. A local-search refinement step swaps

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This paper proposes a Smart Travel Planner and Budget Manager that treats itinerary generation and budget tracking as a single, jointly constrained problem. The system generates a day-wise itinerary under explicit time and distance constraints, estimates its cost from historical fare and tariff data before the trip begins, and continues to track actual expenditure against the estimate once the trip is underway, recommending adjustments whenever a category is projected to exceed its allocation.

The principal contributions of this work are: (1) a constraint-based itinerary generation engine that sequences points of interest under per-day time and travel-distance limits; (2) a cost estimation module that produces a pre-trip budget forecast from historical fare and tariff data; (3) a budget tracking module that compares planned against actual expenditure by category; (4) a recommendation engine that proposes cost-reducing substitutes when a category is projected to overrun; and (5) an empirical evaluation covering itinerary feasibility, cost estimation accuracy, and a twenty-user field trial.

II. RELATED WORK

A. Itinerary Recommendation Systems

Early trip planning tools ranked points of interest by popularity or by proximity to a fixed starting location, leaving sequencing and daily time allocation to the traveller. Later systems modelled itinerary generation as an orienteering problem, maximising visited-attraction value subject to a total time budget, but generally treated monetary cost as a secondary or absent constraint [4], [5].

B. Trip Cost Estimation

Cost estimation for travel has largely been studied within airline and hotel fare-prediction literature, which forecasts price trends for a single booking category rather than an aggregate multi-category trip budget. Regression-based fare models trained on historical booking data have been shown to predict short-horizon price movement with reasonable accuracy, motivating a similar approach for aggregate trip cost estimation [6], [7].

C. Personal Budget Tracking

Personal finance research demonstrates that category-wise tracking with visible progress against a declared limit improves adherence more reliably than a single aggregate spending figure, a finding that directly informs the category-level budget tracking design adopted in this work [8], [9].

D. Constraint-Based Scheduling

Itinerary sequencing under time and distance limits is closely related to the vehicle routing problem with time windows. Greedy nearest-neighbour construction combined adjacent stops when doing so reduces total travel time without violating opening-hour constraints.

E. Cost Estimation Module

Each generated itinerary is costed by summing the historical average tariff for the selected accommodation tier, the fare for the selected transport mode between stops, and the typical activity cost per point of interest, adjusted for the traveller's stated party size. The resulting pre-trip estimate is presented alongside the itinerary before the traveller confirms it.

F. Budget Tracking Module

Once a trip begins, the traveller logs actual expenditure against four categories — accommodation, transport, food, and activities. The module compares cumulative actual spending against the pro-rated planned budget for the elapsed portion of the trip and raises an alert when a category crosses 85% of its allocation ahead of schedule.

G. Recommendation Engine

When a category is projected to overrun, the recommendation engine proposes concrete substitutes drawn from the data layer — a lower-tier accommodation option, an alternative transport mode, or a free or lower-cost point of interest with a similar preference score — together with the estimated saving from each substitution.

IV. METHODOLOGY

A. Dataset Preparation

A dataset of 6,200 points of interest, transport fare records, and accommodation tariffs was assembled across eighteen Indian destinations, combining publicly available tourism board listings with manually verified pricing collected over a two-month period.

B. Itinerary Evaluation Protocol

Itinerary feasibility was evaluated over 500 randomly generated trip requests spanning varied destinations, durations, and pace preferences. A generated itinerary was scored feasible if every day respected the stated time budget and every inter-stop transition respected the maximum travel distance constraint.

C. Cost Estimation Evaluation

Cost estimation accuracy was assessed by comparing the pre-trip estimate against actual recorded expenditure from a twenty-user field trial in which participants planned and completed real trips using the system, logging every expense against its category.

D. Baseline Comparison

A control group of twenty additional participants planned comparable trips using a conventional spreadsheet and manual with local-search improvement has been shown to produce near-optimal daily schedules at a computational cost suitable for interactive, on-demand trip planning [10], [11].

III. SYSTEM ARCHITECTURE

A. Architectural Overview

The proposed system follows a four-layer architecture consisting of a data layer, a planning layer, a budget layer, and a presentation layer, as summarised in Fig. 1. Layer separation allows the itinerary generator and the cost estimator to be retrained or extended independently of the user interface.

research, with planning time and post-trip budget adherence recorded for comparison against the system-assisted group.

E. Evaluation Metrics

Itinerary quality was measured as the feasibility rate across the 500 generated trials. Cost estimation quality was measured using mean absolute percentage error against actual field-trial expenditure. Planning time and budget adherence rate were compared between the system-assisted and control groups.

F. Implementation Environment

The prototype was implemented in Python 3.11 using Flask for the application layer, PostgreSQL for the data layer, and a custom constraint-based scheduler for itinerary generation. The interface was built with HTML5, CSS3, and Chart.js for budget visualisation, and all experiments were executed on a machine with an Intel Core i5 processor and 8 GB of memory.

Fig. 1 — Layered System Architecture of the Proposed Smart Travel Planner and Budget Manager

Layer	Principal Components and Responsibilities
Presentation Layer	Itinerary view, budget dashboard, category progress bars, recommendation cards
Budget Layer	Cost estimation module, expenditure tracker, category alerting, substitution engine
Planning Layer	Preference intake, itinerary generation engine, local-search schedule refinement
Data Layer	Points-of-interest catalogue, fare and tariff records, destination reference database

TABLE I — Comparative Analysis: Manual Spreadsheet vs. Standalone Itinerary App vs. Proposed System

Feature	Manual Spreadsheet Planning	Standalone Itinerary App	Proposed System	Benefit to Traveller
Itinerary Generation	Fully manual research	Automated, budget-unaware	Automated, budget-constrained	Feasible and affordable plan
Cost Estimate	Manual guesswork	Not available	Pre-trip category-wise estimate	Budget known before booking
Expense Tracking	Separate spreadsheet	Not available	Integrated category tracking	Single consistent record
Overrun Alerts	None	None	Category-level threshold alerts	Early corrective action
Recommendations	Not available	Popularity-based only	Cost-aware substitute suggestions	Actionable savings
Consistency	Plan and budget diverge	Plan and budget diverge	Plan and budget jointly maintained	Fewer surprises mid-trip
Planning Effort	High	Moderate	Low	Faster trip preparation

TABLE II — Itinerary Feasibility, Cost Estimation Accuracy, and Field Trial Results

#	Metric	Result	Comparison	Observation
1	Itinerary feasibility rate	97.3%	500 trials	Time and distance constraints respected

#	Metric	Result	Comparison	Observation
2	Cost estimation MAPE	9.2%	Field trial	Against actual recorded expenditure
3	Planning time reduction	26%	System vs. control	Twenty-user comparison
4	Budget adherence — system group	80%	Twenty users	Stayed within declared budget
5	Budget adherence — control group	45%	Twenty users	Spreadsheet-based planning
6	Recommendation acceptance rate	68%	Field trial	Suggested substitutes adopted

V. RESULTS AND DISCUSSION

A. Itinerary Feasibility

As reported in Table II, the itinerary generation engine produced schedules that respected all stated daily time and travel-distance constraints in 97.3% of the 500 generated trials. The remaining infeasible cases were concentrated in requests combining a high point-of-interest density preference with a short trip duration, where the requested pace could not be satisfied within the stated daily time budget regardless of sequencing.

The local-search refinement step reduced total inter-stop travel time by an average of 14.8% relative to the unrefined greedy sequence, confirming that a lightweight improvement pass is worthwhile even within an interactive, on-demand planning context.

B. Cost Estimation Accuracy

The pre-trip cost estimate achieved a mean absolute percentage error of 9.2% against actual recorded field-trial expenditure. Estimation error was lowest for accommodation and transport, which draw on relatively stable tariff and fare records, and highest for the food category, which is most sensitive to individual traveller choice.

C. Field Trial Outcomes

Participants using the full system reported a 26% reduction in planning time relative to the control group and stayed within their declared budget in 80% of trips, compared with 45% for the spreadsheet-based control group. Sixty-eight percent of recommended substitutes offered during a projected overrun were accepted, most commonly a lower-tier accommodation swap.

D. Discussion

The results support the central premise of this work: jointly constraining itinerary generation and budget estimation prevents the two concerns from silently diverging, which is the failure mode that conventional planning tools leave unaddressed. The gap in budget adherence between the system-assisted and control groups suggests that the value of the system lies primarily in surfacing cost information before commitments are made, rather

Group-aware cost modelling that accounts for shared accommodation and transport savings would improve accuracy for family and group travel. Direct booking integration would allow accepted recommendations to be confirmed within the system rather than requiring the traveller to book separately. Finally, extending the platform to a mobile application with offline itinerary access would support travellers in areas with limited connectivity.

VIII. CONCLUSION

This paper presented a Smart Travel Planner and Budget Manager that integrates constraint-based itinerary generation, pre-trip cost estimation, category-wise budget tracking, and cost-aware recommendation within a single system. The itinerary engine produced feasible schedules in 97.3% of 500 generated trials, and the cost estimator achieved a mean absolute percentage error of 9.2% against actual field-trial expenditure.

A twenty-user field trial demonstrated a 26% reduction in planning time and an improvement in budget adherence from 45% to 80% relative to conventional spreadsheet-based planning, indicating that jointly constraining itinerary and budget can materially change planning outcomes. The limitations relating to destination coverage, static pricing data, and the scale of the field trial define a clear agenda for the extensions outlined above. The work shows that treating trip planning and budgeting as a single constrained problem, rather than as two independently managed tasks, can produce itineraries that are both feasible and affordable by design.

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than in the itinerary generation itself. The field trial cohort was small, however, and the observed effect sizes should be treated as indicative rather than conclusive.

VI. LIMITATIONS

Several limitations qualify these findings. First, the points-of-interest and tariff database currently covers eighteen Indian destinations, so both itinerary quality and cost estimation accuracy are expected to degrade for destinations outside this coverage. Second, the cost estimator relies on historical average tariffs and fares, which do not capture seasonal surge pricing or last-minute booking premiums.

Third, the field trial involved twenty system-assisted participants over a limited set of trips and cannot support strong claims about long-term or highly diverse travel patterns. Fourth, the itinerary engine does not currently model group-size-dependent activity costs beyond a linear scaling assumption, which may understate costs for larger travelling parties. Finally, the recommendation engine's substitute suggestions are drawn from a fixed candidate pool and do not yet incorporate real-time availability or booking confirmation.

VII. FUTURE SCOPE

Future development will proceed along five directions. Expanding destination coverage through partnerships with regional tourism boards and booking aggregators would broaden both itinerary quality and cost estimation accuracy. Incorporating live fare and tariff feeds in place of historical averages would allow the cost estimator to react to seasonal and demand-driven pricing.

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