AI Driven Smart Tourism Platform For Personalized Safe and Sustainable Travel Planning

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***Abstract*—Tourism planning remains challenging due to the need for group preference alignment, personalized itineraries, and real-time budget control, which are not adequately supported by existing platforms. This paper presents an AI-driven modular framework that integrates three components: a semantic-aware group recommender using Sentence-BERT embeddings and LightGBM LambdaRank to match travellers; a hybrid itinerary planner combining content-based filtering, collaborative filtering, and XGBoost regression to generate preference-aligned and geographically coherent travel plans; and a predictive budgeting system that applies regression-based forecasting with live API data for dynamic cost estimation. Experiments show strong performance with NDCG@3 = 0.81 for group matching, RMSE = 0.47 and R^2 = 0.77 for itinerary prediction, and a 20–25% improvement in budget accuracy over static baselines. Early user testing further highlights improved satisfaction with itinerary relevance and budget transparency. Overall, the framework demonstrates a scalable and adaptive approach to smart tourism planning, advancing personalization, collaboration, and sustainable travel support.**

***Keywords*—Smart Tourism, Group Recommendation, Hybrid Itinerary, Predictive Budgeting, Machine Learning, Travel Personalization**

I. INTRODUCTION

The tourism industry is rapidly shifting toward personalized, socially engaging, and adaptive experiences, but most existing platforms remain limited to static, individual-focused recommendations. Group travel adds further complexity, as diverse preferences, travel styles, and budget constraints must be balanced in real time. Current systems often fail to support this complexity, leaving travellers without adequate tools for collaborative planning, dynamic itineraries, or responsive cost management.

To address these challenges, this research introduces an AI-driven smart tourism platform that unifies group matching, itinerary generation, and budget allocation into a single adaptive framework. The platform integrates three core modules: a semantic-aware group recommender that identifies compatible travel companions using embeddings and ranking models; a hybrid itinerary planner that combines content-based, collaborative, and machine learning methods to generate preference-aligned and geographically coherent travel plans; and a predictive budget allocator that leverages live data and forecasting models to deliver real-time cost management.

By combining these components into a cohesive system, the platform advances beyond existing tourism solutions, offering scalable, personalized, and collaborative travel planning. Early evaluations further highlight its potential to improve both planning efficiency and traveller satisfaction, while also demonstrating the value of integrating semantic modelling, hybrid recommendation, and real-time predictive analytics within a single tourism framework. This contribution not only enhances personalization and adaptability but also establishes a foundation for future research into sustainable and inclusive smart tourism systems.

In summary, this paper contributes an end-to-end modular framework for smart tourism that integrates group compatibility, itinerary personalization, and predictive budgeting into a unified solution. The work is distinctive in its use of semantic similarity, hybrid recommendation fusion, and live data-driven forecasting, making it one of the first efforts to holistically combine these approaches for both individual and group-based travel planning.

II. LITERATURE REVIEW

A. Collaborative Travel Companion Platform with Intelligent Group Matching

Group recommender systems have gained significance in tourism, where users increasingly seek socially enriched and collaborative travel experiences. Unlike individual recommenders, group-based systems must balance multiple user preferences, introducing additional complexity.[1] proposed a group travel recommender using approximate constraint satisfaction to align individual and collective goals—an approach particularly suited to travel planning, where budget, destination, and style preferences vary across users.

A broader perspective is offered by [2], who categorized group recommendation methods such as score aggregation, clustering, and hybrid strategies in their systematic review. Their taxonomy informed our multi-feature matching approach. Similarly, [3] introduced a personalized group planning model that uses review content and user profiles to suggest compatible travel companions an idea echoed in our use of semantic embeddings and interest alignment.

Hybrid models also show promise. [4] combined collaborative filtering with content-based profiling, enabling robust personalization based on both behavioral and stated preferences. This method aligns with our own hybrid architecture. In a related effort, [5] embedded collaborative filtering into tourism service robots, demonstrating that such algorithms can enhance group interaction even outside conventional software platforms.

User-generated content also contributes to richer profiling. [6] mined traveler attributes and group types from photos, supporting our approach of embedding user interests and locations semantically. Meanwhile, dynamic clustering methods proposed by [7] group users based on travel preferences to recommend personalized routes—an approach we adopt to rank matching travel groups using machine learning.

Finally, cultural sensitivity is another vital component. [8] developed a community-driven, culturally aware recommendation system that tailors suggestions to local contexts. This perspective is especially relevant to our system's deployment in Sri Lanka, where shared cultural expectations influence group dynamics. Collectively, these studies inform our real-time, AI-powered group matching system that integrates personalization, semantic understanding, and collaborative planning.

B. Hybrid Personalized Recommendation and Itinerary Planning System

The adoption of Artificial Intelligence (AI) in tourism has transformed how travel experiences are curated and delivered. Smart tourism, as conceptualized by Gretzel et al. [13], emphasizes technological augmentation of tourism services through personalization, context-awareness, and real-time interactivity. Traditional tourism systems have relied on either content-based filtering (CBF) or collaborative filtering (CF) [11]. While effective individually, these approaches fall short in addressing the complex, multi-dimensional preferences of modern travellers.

Studies such as Duarte et al. [11] and Zhang [16] have highlighted the promise of hybrid approaches that combine multiple AI models. However, their deployment in live systems remains limited due to challenges in technical integration and the complexity of optimizing weighting strategies across methods.

Research from other fields further illustrates AI's potential in tourism. Overgoor et al. [9] demonstrated how AI-driven decision-making supports personalized marketing, a parallel to tourism where individualized insights enhance user engagement. Similarly, Topol [10] explored AI's role in high-stakes domains such as healthcare, suggesting that its decision-making capabilities are equally applicable to the complexities of tourism planning. Yang et al. [14] confirmed that personalized services improve user satisfaction, particularly when both behavioral and contextual data are considered. Yet, Duarte et al. [11] observed that most systems still lack real-time adaptability, often producing static recommendations that fail to adjust to dynamic user needs.

The importance of contextual adaptation is especially evident in emerging tourism economies. Nethmin et al. [15] conducted a data-driven study focused on Sri Lanka, advocating for AI systems that align with local travel patterns and attractions. Their findings underscored the role of geographical coherence, where routing efficiency and cultural context directly shape traveler satisfaction. At the global level, the World Travel & Tourism Council (WTTC) also emphasized the industry-wide shift toward digitization and personalization [12].

Recent machine learning advances provide promising solutions to the limitations of earlier approaches. Gradient boosting algorithms such as XGBoost have achieved strong results in regression tasks involving complex feature interactions, making them well-suited for recommendation problems with interdependent factors. Additionally, integrating demographic profiling with activity-based filtering enables the construction of more nuanced user models. These models capture both explicit preferences and implicit behavioral patterns, improving personalization accuracy.

In light of these insights, this study proposes an end-to-end modular tourism planning framework. The system integrates CBF, CF, and machine learning models into a unified hybrid platform, calibrated specifically for the Sri Lankan tourism landscape. By introducing novel methods for hybrid score combination and geographical corridor-based itinerary generation, the framework addresses both personalization accuracy and practical travel planning constraints.

C. Travel Budget Allocation System for predictive and adjustable cost management

The growing complexity of contemporary travel planning necessitates systems that surpass static spreadsheets and generic budgeting templates. Conventional budget allocation tools often fail to accommodate real-time variables such as fluctuating prices, user-specific preferences, and dynamic tourism trends. As noted by [17], static budgeting frameworks lack the responsiveness to adapt to situational changes, including currency fluctuations and seasonal pricing anomalies.

Recent research underscores the significance of predictive analytics and live data integration in enhancing travel budgeting accuracy. [18] emphasize the utility of API-driven architectures for accessing live pricing data from accommodation and transportation services, which substantially improves the precision of cost estimations. [19] further demonstrates the effectiveness of machine learning algorithms, particularly regression-based models, in forecasting volatile travel expenditures based on both historical data and emerging market patterns.

Equally important is the system's user interface. [20] argue that a user-centric design paradigm significantly increases user engagement and system effectiveness. Interactive and customizable interfaces that allow users to input preferences and receive immediate feedback can elevate user trust and decision-making confidence.

Building on these findings, the integration of predictive algorithms, real-time data streams, responsive interfaces, and intelligent conversational agents (chatbots) forms the foundational framework for next-generation travel budget allocation systems. Beyond adaptive financial planning, the incorporation of a chatbot-driven support mechanism ensures that users remain satisfied with package options and receive real-time guidance, thereby improving overall trust and adoption of the system.

III. METHODOLOGY

The methodology is built on three core modules: a group recommender, a personalized itinerary planner, and a predictive budget allocator. Together, these components form an integrated framework for smart tourism, addressing group compatibility, itinerary personalization, and real-time cost management. The overall system architecture, shown in Figure 1, illustrates how the modules interact through modular APIs and real-time data integration to deliver adaptive and user-centered travel planning.

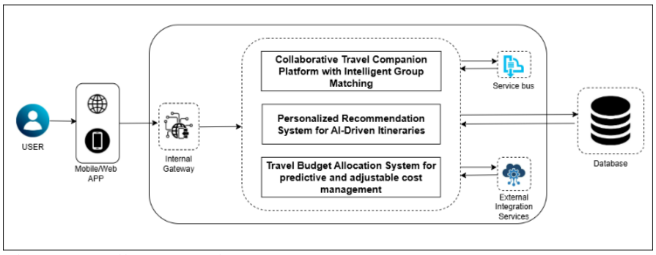

Fig. 1. Overall System Diagram

A. Collaborative Travel Companion Platform with Intelligent Group Matching

This research introduces an intelligent group matching system to support collaborative travel planning by recommending compatible travel groups based on user preferences. The system integrates user profiling, semantic similarity modeling, and learning-to-rank techniques to offer real-time, adaptive recommendations through a modular FastAPI backend. It supports dynamic interaction and is designed for scalability with asynchronous operations and WebSocket-based real-time group chat with AI assistance.

User data was initially gathered through structured survey, collecting information on age, travel interests, preferred destinations, travel style, and budget. Since access to organic group data was limited during early development, synthetic group profiles were generated to simulate real-world diversity. These profiles varied across interests, styles, destinations, and group sizes, enabling effective training of the group recommendation model. As user adoption increases, synthetic data will be replaced with actual behavioural inputs to enhance system personalization and accuracy.

To prepare the data, categorical fields such as budget and travel style were one-hot encoded, and numerical features like age and group size were standardized. Semantic embeddings were generated using Sentence-BERT (SBERT) to encode travel interests and destinations into dense vectors. Cosine similarity was then computed between user and group embeddings to assess alignment. The resulting feature vectors combined numerical, categorical, and semantic data for each user-group pair.

The recommendation model employed LightGBM with a LambdaRank objective to prioritize top-k relevant groups. This model was trained on labeled data indicating user-group matches and evaluated using the NDCG@3 metric to measure ranking quality. When a new user registers, the system computes their profile features and predicts relevance scores across available groups. The top three recommendations are returned, and if no strong match is found (i.e., similarity < 0.65), a new group is created automatically using the user's preferences as its foundation.

All components operate through a modular backend, storing data in MongoDB and ensuring responsive performance via asynchronous endpoints. In addition to recommendations, the system features a real-time group chat module, where users can exchange messages, media files, and travel experiences through WebSockets. An intent classifier, implemented using SBERT embeddings and Logistic Regression, was trained on labeled user intents and achieved an accuracy of 90.7%. This classifier detects intents such as planning trips, sharing experiences, or requesting assistance. The integrated TripBot assistant then responds with relevant travel tips and contextual knowledge.

B. Hybrid Personalized Recommendation and Itinerary Planning System

This work employs a three-stage pipeline comprising a Personalized Recommendation System, a Travel Plan Generator, and a Dynamic Itinerary Builder. The pipeline produces plans that are coherent, preference-aligned, and geographically feasible.

For each user–location pair, the recommender computes a hybrid relevance score by combining content-based filtering (CBF), demographic collaborative filtering (CF), and a supervised machine-learning predictor. In production, CBF compares the user's selected activities with each location's activity profile. The core signal is the fraction of the user's chosen activities that the location supports. This is moderated by how concentrated the location is on those chosen activities (a focus bonus that cannot grow without bound), and a small 10% boost for certain high-salience location types such as beaches, waterfalls, and national parks. The result is a normalized score that rewards both coverage of the user's intent and appropriate specialization of the location.

The CF component forms a demographic neighborhood using age-group, gender, and travel-companion; if no neighbors are found, the filters are progressively relaxed to keep the model robust. Neighbor ratings are average, but if a neighbor's preferred activities fully include the user's requested set, that neighbor's rating gets a 25% multiplicative boost. The final CF score also includes a confidence term that grows with the number of neighbors contributing, so sparse neighborhoods do not dominate the fusion.

The machine-learning component is an XGBoost regressor that predicts a 1–5 rating from a 21-feature vector that includes encoded user demographics (age-group, gender, travel-companion, optional country), location descriptors (type, binary activity flags, activity count), behavioral proxies (average rating, rating count, rating variability), and an activity-match ratio. We use a user-stratified hold-out split, tune with cross-validated randomized search, and persist RMSE/R^2. Predictions are clipped to the valid rating range.

The final relevance is a fixed-weight fusion of the three components: 40% CBF, 35% CF, and 25% ML. CF and ML predictions are first mapped to the same 0–1 range as CBF before fusing. If any component is unavailable for a given pair (e.g., no neighbors), the remaining weights are scaled proportionally so the score remains calibrated.

The Travel Plan Generator consumes a user-curated plan pool together with a Start City, End City, and a corridor radius in kilometers. First, it computes a province-level corridor between the endpoints using a breadth-first search on an adjacency graph. Candidate stops whose perpendicular (crosstrack) distance from the start→end direction exceeds the corridor radius are penalized or filtered. Remaining items are grouped by corridor province and ordered with a greedy forward heuristic that discourages backtracking by penalizing both extra forward distance and deviation from the desired heading; within the final province, items are re-ordered by proximity to the end city. Inter-stop distances use the Haversine formula, and a minimum-attractions guard ensures plan viability.

The Dynamic Itinerary Builder refines that ordered sequence with the same forward-ordering heuristic (we do not apply 2-opt), and, for each stop, proposes corridor-bounded alternatives in several buckets: hybrid-similar, same type, nearby, similar-activities, and top-rated. The "hybrid-similar" bucket blends four normalized signals—vector similarity over location features, set overlap over activities, a distance-based term, and a direct activity-overlap term—with respective weights of 0.2, 0.4, 0.2, and 0.2. This keeps variety high while preserving the corridor constraint.

C. *Travel Budget Allocation System for predictive and adjustable cost management*

The Travel Budget Allocation System is developed as a key module within a broader smart tourism platform. It is designed to deliver adaptive financial recommendations through a combination of machine learning models, real-time data inputs, and user customization. The system is structured into three principal layers: the Data Layer, the Prediction Engine, and the User Interface Layer.

The Data Layer integrates APIs from hotel booking engines, transportation services, and fuel price aggregators. It also leverages historical pricing datasets to support long-term forecasting models. The Prediction Engine employs machine learning algorithms, including regression models and time-series analysis, to estimate upcoming travel costs. Implemented in Python using libraries like Scikit-learn, the models dynamically update forecasts based on live data and evolving user inputs. The User Interface Layer, developed using React, enables users to configure trip parameters such as travel dates, accommodation preferences, and budget tiers. It presents results using intuitive visual elements such as bar charts and pie graphs to aid financial comprehension.

The system development follows a four-phase implementation plan. In the Data Collection phase, real-time API connections are established, and historical data is pre-processed for training. During the Algorithm Development phase, predictive models are built and validated against simulation scenarios, incorporating mechanisms for real-time updating. The User Interface Design phase involves creating interactive dashboards and configurable filters to enhance usability. Finally, the Testing and Evaluation phase comprises unit, integration, and usability testing, including feedback loops for refinement and robustness against edge cases such as sudden price surges or itinerary modifications.

The development leverages a suite of technologies: Python for backend and model implementation; React and Node.js for frontend development; MongoDB for data storage; Dialogflow (or Rasa) for chatbot integration; and third-party APIs for real-time pricing. Tools such as Jest and Selenium are employed for testing, with Jira and Slack for project management. Deployment is facilitated using cloud servers with GPU support to optimize machine learning inference times.

IV. RESULT AND DISCUSSION

A. *Collaborative Travel Companion Platform with Intelligent Group Matching*

The performance of the proposed intelligent group recommendation system was evaluated through quantitative analysis, focusing on how effectively the model ranks and recommends the most suitable travel groups for a given user. The key evaluation metric used was Normalized Discounted Cumulative Gain at rank 3 (NDCG@3), which measures the quality of the top three recommended groups. The trained model achieved an NDCG@3 score of approximately 0.81, indicating that the system reliably prioritizes highly relevant group options in its top recommendations.

This performance validates the use of semantic similarity as a core component of the feature set. The integration of Sentence-BERT embeddings for travel interests and preferred destinations, combined with structured attributes such as age, budget, and travel style, contributed significantly to the model's ability to capture user-group compatibility. The use of cosine similarity in conjunction with LightGBM's LambdaRank objective enabled the system to distinguish subtle differences in user preferences and translate them into accurate ranking scores.

In terms of computational performance, the model demonstrated efficient inference capabilities. The use of LightGBM, known for its speed and scalability, allowed the system to process and rank hundreds of user-group pairs within a short time frame. Pre-computing and caching the SBERT embeddings further reduced response time, making the system suitable for real-time applications where low latency is essential.

An additional mechanism was implemented to handle cases where no existing group yielded a high similarity score. If none of the groups reached a predefined similarity threshold of 0.65, the system automatically triggered a new group creation process. This ensured that every user received a personalized outcome—either by being matched to a compatible group or being assigned to a newly formed one based on their profile attributes.

Beyond recommendation accuracy, The intent classifier achieved an accuracy of 90.7%, confirming its reliability in supporting TripBot responses and enhancing real-time collaboration within travel groups. The TripBot assistant successfully detected intents such as greeting, planning trips, or requesting travel help, and responded with travel tips and suggestions. Experience sharing was supported by an automated flush mechanism, which captured user-contributed travel tips and stored them for future retrieval. File sharing (images, videos, documents, audio) was seamlessly handled using MongoDB GridFS.

The overall system, combining semantic modeling, learning-to-rank optimization, and real-time computation, provides a robust solution for collaborative travel planning. The achieved results confirm the system's capability to support meaningful and personalized group recommendations, aligning with the project's objective of improving group-based travel experiences through intelligent automation.

B. Hybrid Personalized Recommendation and Itinerary Planning System

The hybrid recommendation engine delivered strong predictive accuracy on a user-stratified hold-out, with RMSE = 0.48 and R^2 = 0.77, indicating reliable alignment between predicted and observed ratings. The training set comprised ≈10,673 users, 76 locations, and ≈16,156 reviews, with 21 engineered features spanning encoded demographics, location descriptors (type, activity flags, activity count), behavioral proxies (average rating, rating count, variability), and an activity-match ratio.

Beyond the supervised model, the inclusion of content-based filtering (CBF) and demographic collaborative filtering (CF) added complementary signals: CBF emphasized coverage of the user's selected activities with a bounded focus bonus and a modest type boost for high-salience categories, while CF aggregated peer ratings within progressively relaxed demographic neighborhoods and applied a 1.25× boost when neighbor preferences fully included the user's requested activities. Fusing the three components with fixed deployment weights (0.40 CBF / 0.35 CF / 0.25 ML; CF/ML normalized to the 0–1 range) improved robustness under sparse neighborhoods and preserved personalization fidelity.

Functionally, the end-to-end pipeline returned top destinations consistent with individual preferences (e.g., well-known national parks and biodiversity sites), then organized them into province-aware travel corridors between the chosen start and end cities. The Travel Plan Generator filtered items by a user-defined corridor radius, discouraged backtracking via a heading-aware forward ordering, and computed inter-stop distances with the Haversine formula. The Dynamic Itinerary Builder refined the sequence and surfaced bounded alternatives in several buckets (hybrid-similar, same type, nearby, similar-activities, top-rated) to maintain variety without violating corridor constraints. Practical safeguards—such as a minimum-attractions check with actionable guidance—provided clear feedback when inputs were insufficient for a viable plan.

Overall, the system's strengths are its multi-layered personalization, geospatial coherence, and graceful degradation when data are sparse. Remaining limitations include the lack of learned fusion weights, route re-optimization beyond greedy ordering (e.g., 2-opt), and omission of ranking-quality metrics (Precision@k, nDCG@k) and detour factor—each a target for future work alongside time-window constraints and travel-time models.

C. Travel Budget Allocation System for predictive and adjustable cost management

Early-stage development and preliminary system evaluations have yielded encouraging results. Simulation tests revealed that the predictive models improved cost estimation accuracy by approximately 20–25% compared to traditional static budgeting tools. The system's responsiveness to real-time inputs was notable, with cost forecasts updating in under two seconds across diverse travel scenarios.

Initial user testing conducted with a small cohort of travelers demonstrated enhanced satisfaction, particularly with the intuitive filtering options and the visual clarity of the budget breakdowns. The tiered budgeting options—categorized into Basic, Moderate, and Premium—allowed users to align their travel plans with financial constraints. The system also exhibited high adaptability, effectively recalibrating budget recommendations in response to last-minute changes such as altered travel dates or switching from hotel to hostel accommodations.

Visualizations played a critical role in improving decision-making. Users reported reallocation of spending such as increasing accommodation budgets after viewing under allocation in the initial breakdown highlighting the system's impact on budget optimization behaviour.

These findings validate the architectural design and predictive methodology of the Travel Budget Allocation System. Moreover, the integration of a budget-planning chatbot enhances trust, usability, and user satisfaction, positioning the system as a robust and user-responsive solution within the smart tourism ecosystem.

To assess the effectiveness of the proposed framework, we evaluated each module using widely accepted performance metrics. Table I summarizes the results across group recommendation, itinerary planning, and predictive budgeting. Collectively, the system demonstrates strong performance, achieving accurate group matching, coherent and preference-aligned itineraries, and significantly improved budget forecasts compared to traditional baselines. These outcomes validate the framework's ability to deliver a unified, AI-driven solution for smart tourism planning.

TABLE I. Evaluation Metrics for System Modules

Module	Metric	Result
Group Recommender	NDCG@3	0.81
TripBot Intent Classifier	Accuracy	0.90
Itinerary Planner	RMSE	0.47
Itinerary Planner	R^2	0.77
Budget Predictor	R^2	0.87
Budget Predictor	Accuracy Gain	20-25%

V. CONCLUSION

This study presented an AI-powered smart tourism platform that unifies group matching, itinerary generation, and predictive budgeting into a single adaptive framework. Unlike conventional systems that provide static or individual-focused recommendations, the proposed approach integrates semantic modelling, hybrid recommendation techniques, and real-time forecasting to support more collaborative and flexible travel planning.

The evaluation demonstrated that the system could generate reliable group recommendations, coherent and preference-aligned itineraries, and accurate budget predictions, validating its potential as a practical tool for travellers. Beyond technical performance, the platform also emphasizes usability, with features such as real-time group interaction, adaptive itinerary adjustments, and intuitive budget visualizations, which were positively received in early user testing.

Looking ahead, further development will focus on scaling evaluations with real-world user data, incorporating multi-lingual and culturally adaptive features, and integrating advanced optimization for routing and scheduling. These improvements aim to enhance inclusivity and efficiency, making the platform adaptable to diverse travel contexts.

Overall, this research lays the foundation for a new generation of intelligent, interactive, and user-centered tourism systems, capable of meeting the evolving needs of modern travellers while promoting personalization, collaboration, and sustainable tourism practices.

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