AI DRIVEN SMART TOURISM PLATFORM FOR PERSORNALIZED SAFE & SUSTAINABLE TRAVEL PLANNING

Project ID: R25-006

Project Final Report

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Department of Software Engineering

Sri Lanka Institute of Information Technology Sri Lanka

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Dissertation submitted in partial fulfilment of the requirements for the Bachelor of Science (Hons) in Information Technology Specializing in Software Engineering

Department of Software Engineering

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DECLARATION

We declare that this is our own work, and this Thesis does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other University or institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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29/08/2025

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Date

28-08-2025

Signature of co-supervisor

(Ms. Karthiga Rajendran)

Date

ABSTRACT

As tourism becomes increasingly collaborative, there is a growing demand for intelligent systems that support group-based travel planning while offering personalized, real-time recommendations. Traditional platforms often provide static itineraries or individual suggestions, which fail to accommodate the diverse preferences of groups, adapt to dynamic pricing, or ensure sustainable travel experiences. To address these challenges, this project presents a modular AI-driven tourism platform that integrates three core components: a collaborative group recommender that matches travellers into compatible groups using semantic similarity modelling, user profiling, and a LightGBM-based learning-to-rank model; a personalized itinerary planner that combines content-based filtering (CBF), collaborative filtering (CF), and an XGBoost predictor to recommend, sequence, and optimize tourist attractions along realistic travel corridors; and a dynamic travel budget allocator that predicts and adjusts trip costs in real time using regression-based forecasting, API-driven pricing integration, and interactive visualization. The system emphasizes semantic understanding, geospatial alignment, and user interaction through real-time APIs and WebSocket-based collaboration features. By combining personalization, adaptability, and cultural context, the platform supports both individual and group travellers in creating coherent, safe, and sustainable travel plans. Collectively, these modules deliver a cohesive and future-ready solution tailored to the Sri Lankan tourism context, while offering scalability for broader global applications.

Keywords: Smart Tourism, Group Recommender System, Itinerary Planning, Budget Forecasting, Machine Learning, Semantic Similarity.

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LIST OF ABBREVIATIONS

Abbreviations	Description
AI	Artificial Intelligence
API	Application Programming Interface
DB	Database
FastAPI	Fast Application Programming Interface
GPU	Graphics Processing Unit
ML	Machine Learning
NDCG	Normalized Discounted Cumulative Gain
WS	WebSocket
CI/CD	Continuous Integration / Continuous Deployment
UAT	User Acceptance Testing

1. INTRODUCTION

1.1 Background Study and Literature Review

1.1.1 Background Study

Tourism is one of the world's fastest-growing industries and has become a vital sector for many economies, particularly in developing countries such as Sri Lanka. In recent years, the industry has witnessed a paradigm shift from static and generic services to personalized, interactive, and collaborative experiences. With the rise of digital platforms, travellers are increasingly expecting intelligent tools that can understand their unique preferences, adapt to changing conditions, and provide seamless planning experiences. This demand has driven significant interest in the adoption of Artificial Intelligence (AI) and data-driven technologies to enhance tourism services.

Traditional tourism systems are often limited in scope. Most existing platforms focus on static itinerary generation or individual recommendations that fail to capture the complexities of group-based travel. Group travel introduces unique challenges, as it requires balancing diverse preferences in terms of destinations, budgets, travel styles, and activity choices. In the Sri Lankan context, where cultural and regional diversity strongly influence travel behaviour, this complexity is even more pronounced. For example, while one group member may prefer cultural heritage sites, another may prioritize adventure or eco-tourism activities. Conventional systems, which rely mainly on generic content delivery or manual planning, lack the intelligence to reconcile these competing preferences in real time.

Another significant limitation of current tourism platforms is the absence of adaptability. Many platforms provide fixed recommendations that do not update in response to real-time factors such as fluctuating travel costs, seasonal variations, or last-minute changes in user preferences. This rigidity results in reduced user satisfaction and inefficiency in resource allocation. For instance, budget planning is usually carried out with static spreadsheets or templates that fail to incorporate dynamic variables such as accommodation price fluctuations, transport delays, or sudden currency changes. As a result, travellers often encounter financial mismatches between their initial plans and actual expenditures.

Advancements in AI and machine learning have opened new avenues for addressing these challenges. Techniques such as collaborative filtering (CF), content-based filtering (CBF), and hybrid approaches have shown promising results in personalizing recommendations for individual travellers. However, extending these methods to group settings requires additional layers of semantic modelling, compatibility assessment, and adaptive ranking. Recent research has highlighted the importance of semantic similarity modelling through embeddings such as Sentence-BERT (SBERT), which enables systems to capture not only surface-level attributes but also deeper contextual alignments between users and destinations. When combined with ranking algorithms like LambdaRank and gradient boosting methods such as LightGBM, these models provide the foundation for intelligent group formation and recommendation.

Similarly, itinerary planning has evolved from simple rule-based sequencing of attractions to more advanced models that integrate user profiling, behavioural data, and geographical coherence. Hybrid recommendation engines that fuse CBF, CF, and machine learning predictors are capable of producing travel plans that are not only preference-aligned but also geographically feasible. For instance, applying geospatial methods such as the Haversine formula allows for realistic distance calculations, while corridor-based sequencing avoids unnecessary detours and optimizes travel efficiency. These improvements represent a significant advancement over static itineraries, offering travellers dynamic and context-aware planning experiences.

Budget allocation is another critical area where AI can make a substantial impact. Conventional budgeting tools are incapable of adapting to real-time changes, often leading to over- or under-estimation of expenses. By leveraging regression-based forecasting, time-series modelling, and live API integration from hotels, transportation providers, and fuel aggregators, modern systems can provide adaptive and personalized financial planning. Such systems can predict expenditure patterns, adjust allocations on the fly, and offer visual dashboards for transparency. The integration of conversational agents further enhances usability, allowing travellers to interact with the system naturally and receive immediate guidance.

In addition to technical advancements, the social dimension of tourism must also be considered. Group travel is not only about destinations and costs but also about collaboration, communication, and shared experiences. Features such as real-time group chats, intelligent assistants, and intent classifiers support interactive collaboration during planning. In our proposed system, the TripBot assistant acts as a facilitator, identifying user intents (e.g., planning trips, sharing experiences, requesting help) with high accuracy and providing relevant suggestions. This ensures that group planning remains engaging, cohesive, and contextually relevant.

The Sri Lankan tourism landscape provides an ideal setting for such an intelligent platform. As a country with rich cultural heritage, biodiversity hotspots, and diverse regional attractions, Sri Lanka attracts a wide range of travellers with varying expectations. However, many tourists—both local and international—face challenges in identifying optimal travel routes, balancing budgets, and aligning group interests. An AI-powered smart tourism platform tailored for Sri Lanka can bridge this gap by combining personalization, cultural awareness, and adaptability. Such a system not only improves user satisfaction but also contributes to sustainable tourism by promoting efficient resource usage, reducing unnecessary travel detours, and encouraging context-aware recommendations.

Overall, the background to this research highlights a clear shift in tourism demands and technological opportunities. The limitations of traditional systems—including static itineraries, lack of group support, and absence of adaptive budgeting—underscore the necessity of innovative solutions. At the same time, advancements in AI, semantic modelling, and predictive analytics offer a promising foundation for addressing these gaps. By integrating these technologies into a unified platform, this project seeks to transform how travellers, particularly in Sri Lanka, plan and experience tourism. The proposed system's focus on collaboration, personalization, and real-time adaptability positions it as a forward-looking solution that aligns with global trends while catering to local needs.

1.1.2 Literature Review

Tourism research has increasingly focused on developing intelligent systems that enhance personalization, collaboration, and adaptability in travel planning. With the rapid growth of digital platforms, travelers today expect solutions that not only recommend destinations but also adapt to real-time constraints such as group dynamics, fluctuating costs, and contextual factors. Existing literature across recommender systems, itinerary generation, and budget management highlights both the progress made and the limitations that remain, motivating the need for more comprehensive frameworks such as the one proposed in this study.

Group recommender systems have gained significant attention in the tourism domain, where users increasingly seek socially enriched and collaborative travel experiences. Unlike individual recommenders, group-based systems must balance diverse preferences, introducing additional complexity. One study proposed approximate constraint satisfaction to align individual and collective goals, a method particularly suited to balancing budget, destination, and style preferences within group travel [1]. Another review categorized group recommendation methods such as score aggregation, clustering, and hybrid strategies, offering a taxonomy that has informed multi-feature approaches in real-world systems [2]. Additional research introduced personalized group planning models based on review content and user profiling, demonstrating the value of semantic embeddings and interest alignment [3]. Hybrid models that combine collaborative filtering with content-based profiling [4] have shown strong potential for robust personalization. Beyond software platforms, collaborative filtering has even been embedded into tourism service robots, illustrating how such algorithms can support group interaction in unconventional contexts [5]. User-generated content has also proven valuable for group recommendation, with one study mining traveler attributes and group types from photos to support semantic embeddings of user interests and locations [6]. Meanwhile, dynamic clustering methods have been applied to enable personalized route planning by grouping users according to travel preferences [7]. Cultural sensitivity has also emerged as a critical factor, with community-driven, culturally aware recommendation systems demonstrating how local contexts can influence group dynamics [8]. These studies collectively highlight the importance of personalization, semantic understanding, and cultural alignment in building effective group recommender systems.

Parallel to advances in group recommendation, significant research has also been conducted on personalized itinerary planning. Smart tourism emphasizes personalization, context-awareness, and real-time interactivity [13]. Traditional tourism recommenders have typically relied on content-based filtering (CBF) or collaborative filtering (CF) [11]. While these methods are individually effective, they struggle to address the multidimensional preferences of modern travelers. Hybrid approaches that integrate multiple models have been shown to outperform single techniques [11], [16]. Beyond tourism, studies in adjacent fields reinforce the applicability of AI, where AI-driven decision-making has been successfully applied in domains such as marketing and healthcare [9], [10]. Personalized services have also been shown to improve satisfaction when behavioral and contextual data are jointly considered [14]. Research focused specifically on Sri Lankan tourism emphasized the importance of geographical coherence and local cultural context [15], while global organizations highlighted the industry-wide shift toward digitization and personalization [12]. Modern machine learning methods, particularly gradient boosting models such as XGBoost, have proven effective for recommendation problems involving complex feature interactions [16]. Integrating demographic profiling with activity-based filtering enables richer user models that capture both explicit preferences and implicit behaviors, thereby enhancing recommendation accuracy. Collectively, these studies provide a foundation for building modular frameworks that combine CBF, CF, and supervised learning to generate itineraries that are not only personalized but also geographically feasible and contextually aligned.

In addition to group matching and itinerary generation, travel budgeting is a crucial dimension of tourism planning. Conventional budget allocation tools are static and fail to account for the dynamic nature of tourism costs. Static spreadsheets and templates lack responsiveness to real-time changes such as currency fluctuations or seasonal price anomalies [17]. Recent studies emphasize the role of predictive analytics and live data integration in overcoming these limitations [18], [19]. The role of user experience design is also well documented, as user-centric interfaces that enable travelers to configure preferences and receive immediate feedback significantly increase engagement and trust [20]. These insights underline the need for adaptive budget planning tools that combine predictive algorithms, real-time data streams, and intuitive interfaces. The incorporation of conversational agents, such as chatbots, further enhances usability by ensuring that users receive real-time guidance and package adjustments tailored to their needs.

In summary, the literature demonstrates significant advances across group recommendation, itinerary planning, and budget allocation. However, most existing systems treat these dimensions in isolation, resulting in fragmented solutions. Very few frameworks integrate group compatibility, personalized itinerary generation, and adaptive budgeting into a unified platform, especially in the context of Sri Lankan tourism. This gap motivates the design of the proposed AI-driven smart tourism platform, which combines semantic modelling, hybrid recommendation, predictive budgeting, and real-time collaboration to create a cohesive, user-centric solution.

1.2 Research Gap

Tourism technology has advanced significantly with the integration of recommender systems, itinerary planning tools, and digital budgeting platforms. However, an in-depth review of existing literature and currently available solutions reveals several gaps that remain unaddressed.

Firstly, group recommender systems in tourism are still in their early stages. While research has introduced methods such as score aggregation, clustering, and hybrid strategies, most platforms continue to operate on an individual recommendation basis. Existing systems rarely account for the complexities of group decision-making, such as aligning diverse preferences, balancing budgets, and resolving conflicts in travel styles. Furthermore, cultural and contextual sensitivity remains underexplored, especially in regions like Sri Lanka where group dynamics are strongly influenced by shared cultural norms. This lack of real-world, group-centered recommendation limits the applicability of existing tools in collaborative travel scenarios.

Secondly, itinerary planning systems suffer from rigidity and a lack of contextual awareness. Traditional models using either content-based filtering or collaborative filtering provide static suggestions that do not adjust to real-time conditions or dynamic user preferences. Even hybrid approaches, while theoretically more accurate, are seldom deployed in live systems due to integration challenges and computational overhead. Moreover, existing solutions often neglect geospatial coherence, leading to impractical travel routes that either backtrack or ignore travel-time feasibility. In the Sri Lankan context, this issue is particularly pressing, as inefficient travel corridors can lead to wasted time, higher costs, and reduced user satisfaction.

Thirdly, travel budgeting tools remain largely static. Many travellers rely on spreadsheets or basic calculators that do not incorporate fluctuating variables such as accommodation prices, seasonal changes, or transportation costs. Even modern budgeting applications often fail to integrate predictive analytics or real-time API data, resulting in inaccurate forecasts. Furthermore, most platforms lack interactive and user-friendly interfaces that allow travellers to adjust preferences on the fly. The absence of adaptive budgeting mechanisms restricts travellers from making informed financial decisions during trip planning, often leading to overspending or poorly optimized itineraries.

Finally, the integration of these three critical dimensions—group formation, itinerary personalization, and dynamic budgeting—into a unified platform is virtually absent in the current tourism technology landscape. Existing tools tend to address each problem in isolation, creating fragmented experiences that require travellers to rely on multiple disconnected applications. This siloed approach hinders seamless planning and fails to reflect the interconnected nature of real-world travel.

In summary, the research gap lies in the lack of an end-to-end, AI-driven smart tourism platform that simultaneously addresses group compatibility, personalized itinerary generation, and adaptive budgeting within a culturally and geographically coherent framework. This gap highlights the need for the proposed system, which leverages semantic modelling, hybrid recommendation techniques, predictive analytics, and real-time interaction to deliver a cohesive, user-centric solution tailored to the Sri Lankan tourism context.

1.3 Research Problem

Tourism plays a crucial role in economic growth and cultural exchange, yet the planning process remains a major challenge for both individual and group travelers. In particular, group travel introduces complex decision-making scenarios, as preferences, budgets, and expectations vary widely among participants. Traditional digital platforms have attempted to address aspects of this process—such as providing generic itineraries or simple cost calculators—but they often fall short of meeting the real needs of modern travelers.

One critical problem lies in group compatibility and decision-making. Existing platforms predominantly cater to individual users and lack robust mechanisms to match travelers into compatible groups. In collaborative travel, multiple preferences regarding destinations, activities, and budget constraints must be balanced. Current systems do not adequately capture these diverse attributes, nor do they provide real-time adaptability to resolve conflicts within group dynamics. As a result, travelers are often forced to rely on manual coordination, which is time-consuming and prone to disagreements.

A second major issue concerns the rigidity of itinerary planning**.** Current systems typically generate static recommendations that do not account for changing contexts such as seasonal variations, travel time, or evolving user inputs. Even where personalization is attempted through content-based or collaborative filtering, the resulting itineraries often lack geographical coherence. For example, attractions may be recommended without considering travel corridors, leading to backtracking, excessive travel times, and ultimately poor user satisfaction. Particularly in Sri Lanka, where attractions are geographically dispersed, inefficient routing can increase costs, waste time, and undermine the overall travel experience.

The third problem area is financial planning for travel**.** Most existing tools rely on static budgeting templates or manual calculations, which fail to account for real-time cost fluctuations in accommodation, transport, and activities. Travelers are often left with inaccurate cost estimates that do not reflect current market conditions, resulting in overspending or the need to make last-minute compromises. Furthermore, the lack of interactive and predictive features means travelers cannot proactively adjust their financial plans to accommodate changes in preferences or circumstances.

The absence of integration across these three dimensions—group recommendation, itinerary planning, and budget allocation—creates a fragmented and inefficient planning process**.** While isolated solutions exist for each component, they rarely work together in a unified framework. This fragmentation forces travelers to rely on multiple disconnected platforms, increasing planning complexity and reducing the effectiveness of the travel experience.

In the Sri Lankan context, these challenges are particularly significant. The country's diverse tourism offerings—ranging from cultural heritage sites to nature reserves and adventure destinations—require careful coordination to ensure meaningful and cost-effective travel experiences. Yet, travelers often lack access to intelligent tools that consider both local travel patterns and cultural contexts while supporting collaboration, personalization, and financial adaptability.

Therefore, the research problem addressed in this project is the lack of an integrated, AI-driven smart tourism platform that can simultaneously support group formation, generate personalized and geographically coherent itineraries, and provide adaptive budget management**.** Without such a solution, travelers face inefficiencies, poor alignment of group expectations, inaccurate financial planning, and limited personalization, ultimately reducing satisfaction and hindering the potential of Sri Lanka's tourism industry.

1.4 Research Objectives

1.4.1 Main Objective

The main objective of this research is to design and develop an AI-driven smart tourism platform that enables collaborative, personalized, and sustainable travel planning for both individuals and groups. The system aims to integrate intelligent group matching, personalized itinerary generation, and dynamic budget allocation into a single cohesive platform, thereby addressing the limitations of existing fragmented solutions.

1.4.2 Specific Objectives

The specific objectives of this research are to:

- Develop a collaborative group recommender that matches travelers into compatible groups using semantic similarity modeling, user profiling, and a LightGBM-based learning-to-rank algorithm.
- Design and implement a personalized itinerary planner that integrates content-based filtering (CBF), collaborative filtering (CF), and machine learning (XGBoost regression) to generate geographically feasible and preference-aligned travel plans.
- Incorporate geospatial coherence techniques, including Haversine distance calculations and corridor-based sequencing, to ensure efficient and realistic routing.
- Build a dynamic budget allocation module that uses regression-based forecasting, real-time API integration, and interactive dashboards to predict, monitor, and adapt trip costs.
- Integrate a real-time conversational assistant (TripBot), powered by intent classification, to support user collaboration and provide contextual travel guidance within groups.
- Ensure the platform is scalable and user-friendly by employing a modular system architecture with FastAPI, React, and MongoDB for real-time performance and responsiveness.

- Evaluate system performance using key metrics such as NDCG for group matching, RMSE and R^2 for itinerary prediction, and accuracy improvements for budget forecasting.

1.4.3 Business Objectives

In addition to technical objectives, the platform is designed with several business-oriented goals to ensure practical applicability and long-term sustainability:

- Introduce a scalable and market-ready tourism solution that caters to the Sri Lankan travel industry, addressing both local and international travelers.
- Position the platform as a leading AI-driven travel planning tool by offering unique features such as group compatibility, hybrid itinerary generation, and adaptive budgeting that differentiate it from generic platforms.
- Generate revenue through subscription tiers, institutional partnerships with travel agencies, and premium features such as advanced analytics, guided trip planning, and cultural recommendations.
- Expand the system beyond Sri Lanka by scaling to multilingual and multi-regional versions, allowing adoption across South Asia and other emerging tourism markets.
- Support sustainable tourism practices by promoting optimized travel routes, cost-effective planning, and culturally sensitive recommendations, thereby contributing to the long-term growth of the industry.
- Build opportunities for collaboration with government bodies, tourism boards, and private stakeholders to position the platform as a trusted digital ecosystem for travel planning.

2. METHODOLOGY

2.1 Introduction

This chapter outlines the methodology adopted in designing and developing the AI-driven smart tourism platform. The project followed a structured research and development process to ensure that the system met both functional and non-functional requirements. A combination of Agile development practices, user-centered requirement gathering, and modular system design was employed to achieve the research objectives.

The methodology integrates both theoretical research and practical implementation. Literature findings were first analysed to identify existing gaps in group recommendation, itinerary planning, and budget allocation. These insights informed the design of system components. Each module was then developed using machine learning and natural language processing techniques, integrated through a service-oriented backend, and validated via user testing and performance evaluation.

2.2 System overview

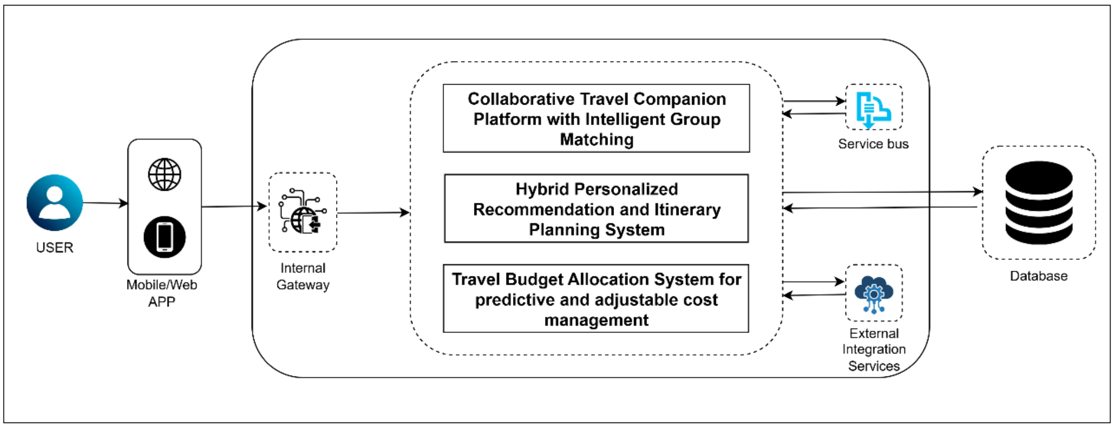

Figure 1: The system diagram of the system

2.3 Component Overview

Component 1: Collaborative Travel Companion Platform with Intelligent Group Matching

This component is designed to enable travellers to be matched into compatible groups by analysing demographic, behavioural, and interest-based attributes. It leverages advanced semantic modelling and ranking techniques to recommend the most suitable groups in real time. Figure 2 illustrates the system overview of this component.

Methodology**:**

- User Profiling: Collects demographic details such as age group, travel style, budget range, and preferred activities.
- Semantic Embeddings: Encodes user interests and destinations using Sentence-BERT (SBERT) embeddings.
- Ranking Model: Employs a LightGBM model with LambdaRank objective to rank potential group matches. The model was evaluated using the NDCG@3 metric.
- Real-Time Group Chat: Implements WebSocket-based group communication to enhance collaboration among members.
- Intent Classifier: Trained on SBERT embeddings with Logistic Regression, the classifier detects conversation intents such as trip planning, sharing experiences, or requesting support, achieving an accuracy of 90.7%.
- TripBot Assistant: Responds contextually to detected intents, providing travel tips, suggestions, and guidance, thereby improving group decision-making.

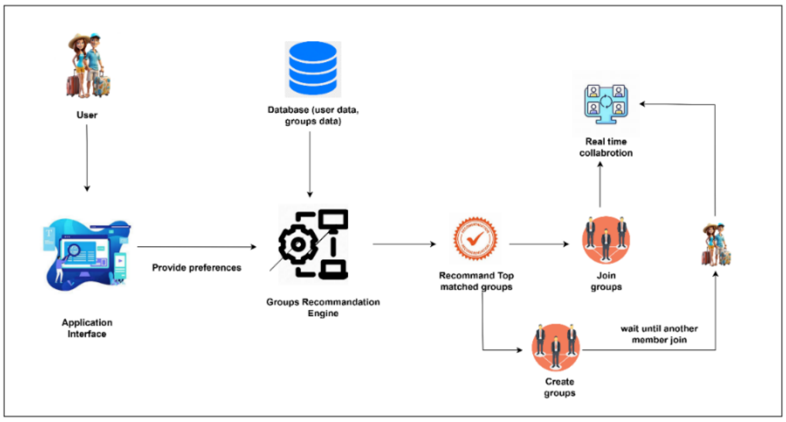

Figure 2: System diagram for collaborative platform

Component 2: Hybrid Personalized Recommendation and Itinerary Planning System

This component generates personalized travel itineraries that are both preference-aligned and geographically feasible. It integrates multiple recommendation techniques into a unified hybrid framework to ensure accuracy and practicality. Figure 3 illustrates the system overview of this component.

Methodology:

- Content-Based Filtering (CBF): Compares a user's chosen activities against each location's activity profile.
- Collaborative Filtering (CF): Aggregates peer ratings from demographically similar travelers.
- Machine Learning (ML): Uses an XGBoost regressor trained on 21 engineered features including demographics, activity flags, ratings, and activity ratios.
- Hybrid Scoring**:** Relevance is computed using fixed weights: 40% CBF, 35% CF, and 25% ML.
- Geospatial Coherence: Applies Haversine distance calculations and corridor-based sequencing to avoid backtracking in generated itineraries.
- Dynamic Itinerary Builder: Provides alternative suggestions grouped into categories such as nearby attractions, same type, hybrid-similar, and top-rated.

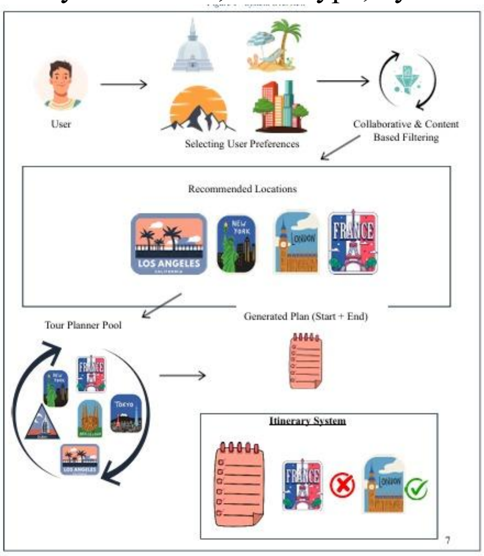

Figure 3: System diagram for Recommendation and Itinerary Planning System

Component 3: Travel Budget Allocation System for predictive and adjustable cost management

This component provides adaptive and real-time financial planning support for travelers by integrating predictive models with live data feeds. It ensures that travel budgets remain accurate, flexible, and user-friendly. Figure 4 illustrates the system overview of this component.

Methodology:

- Data Layer: Integrates APIs from hotels, transportation services, and fuel aggregators, alongside historical pricing datasets for forecasting.
- Prediction Engine: Implements regression-based forecasting and time-series analysis using Scikit-learn to estimate upcoming travel costs dynamically.
- User Interface Layer: Provides interactive dashboards built with React that display cost breakdowns through visualizations such as bar and pie charts.
- Chatbot Integration: Includes a conversational assistant to answer user queries and suggest financial adjustments.
- Evaluation: Simulation tests revealed a 20–25% improvement in cost estimation accuracy compared to static methods. Initial user testing confirmed the usefulness of tiered budgeting (Basic, Moderate, Premium) and highlighted the system's responsiveness to last-minute plan changes.

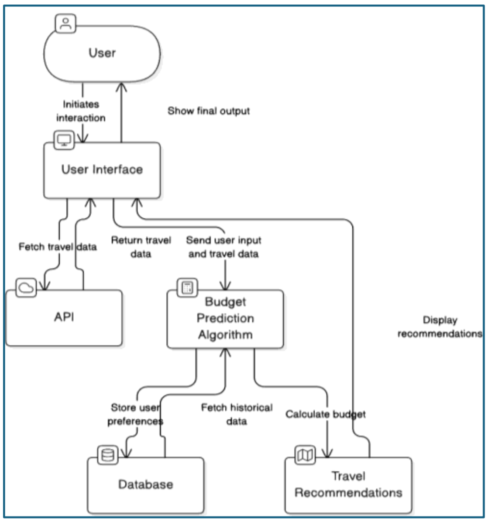

Figure 4: System diagram for Budget Allocation System

2.3 Development Process

The development of the AI-Driven Smart Tourism Platform, a personalized and collaborative web-based travel planning system for Sri Lankan and international travelers, followed the **Agile development methodology**. Agile's iterative, feedback-driven approach was ideal for this project, where flexibility, rapid prototyping, and continuous refinement were crucial to meet evolving user requirements and ensure robust integration across group recommendation, itinerary planning, and budget allocation modules. Below is an overview of how the Agile process was applied during the development of the platform:

1. Project Initiation

The project began with a clear objective: to develop an intelligent travel planning platform that supports group matching, personalized itinerary generation, and dynamic budget allocation. The scope was defined to ensure a modular architecture that could be expanded to support real-time interaction, cultural sensitivity, and future scalability.

2. Product Backlog Creation

A product backlog was created containing prioritized features, user stories, and technical tasks across different modules including collaborative group recommender, hybrid itinerary planner, budget allocator, and TripBot conversational assistant. The backlog was updated regularly based on internal reviews, feedback from tourism experts, and early-stage user surveys conducted during requirement analysis.

3. Sprint Planning

The development timeline was divided into multiple sprints; each focused on building and refining specific features or components. In sprint planning meetings, tasks were selected from the backlog based on priority and feasibility. Clear sprint goals and estimated workloads were defined for each cycle.

4. Daily Standup Meetings

The team conducted short daily standups to discuss task progress, resolve blockers, and align development objectives. These meetings promoted collaboration between developers, data engineers, and UI/UX designers, ensuring consistent momentum throughout each sprint.

5. Development and Testing

Developers implemented core functionalities such as the SBERT + LambdaRank group recommender, hybrid itinerary planner (CBF + CF + XGBoost), geospatial routing, and budget predictor using regression + API integration. Testing was conducted in parallel to development — unit, module, integration, and system testing were performed to ensure functional accuracy and stability.

6. Collaboration and Feedback

Continuous collaboration was maintained among developers, supervisors, and tourism domain experts. Periodic demos were held to showcase progress to stakeholders, including frequent travelers and tourism agents, allowing the team to incorporate real-time feedback and refine the system.

7. Review and Adaptation

At the end of each sprint, review meetings were conducted to present completed features and gather stakeholder feedback. A sprint retrospective was held to assess what worked well and what could be improved in the next iteration.

8. Continuous Integration and Deployment

Features were integrated continuously to ensure code compatibility and smooth functioning across modules. GitHub Actions pipelines were used for automated builds and deployments to cloud servers, allowing quick testing of new updates and maintaining a stable development environment.

9. Scaling and Release

As development progressed, new features such as TripBot integration, tiered budgeting options, and alternative itinerary suggestions were added and refined based on stakeholder input and testing outcomes. The platform was prepared for pilot release to a broader user base, with scalability in mind to accommodate future expansions such as multilingual support and mobile applications.

10. Ongoing Improvement

Following Agile's principle of continuous improvement, the team regularly reviewed workflows, refined backlogs, and enhanced product quality. This cycle of iterative development, validation, and enhancement continues to drive the evolution of the AI-Driven Smart Tourism Platform as a modern, intelligent, and user-centric travel planning system.

By adopting Agile methodology, the development team ensured a flexible, adaptive, and user-focused process that responded effectively to technical challenges while addressing the real-world needs of modern travellers. Figure 5 shows the Agile-based development life cycle used for the Smart Tourism Platform.

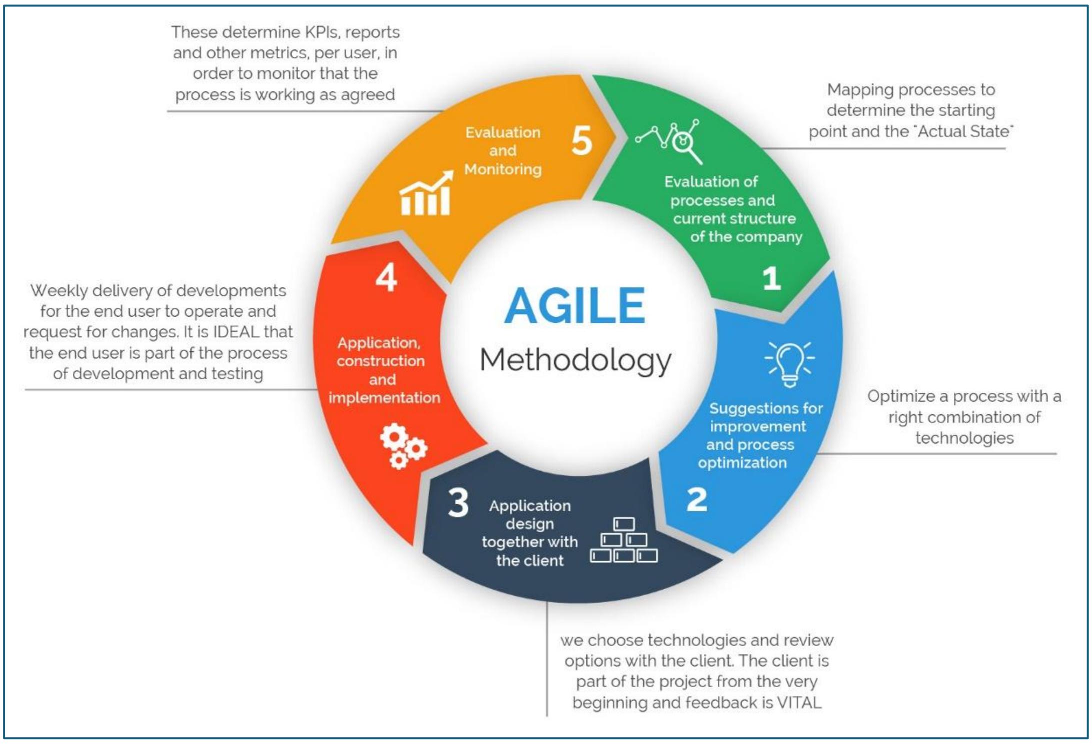

Figure 5: Agile based development lifecycle

2.3.1 Project Management

Effective project management and version control were crucial to the successful development of the AI-Driven Smart Tourism Platform. The team employed **Jira** for task management and sprint planning, and **GitHub** for version control, ensuring efficient collaboration, timely deliveries, and consistent progress tracking throughout the project lifecycle.

1. Task Planning and Organization

Jira served as the central platform for managing all development tasks. Epics and user stories were created for major components such as the Collaborative Group Recommender, Hybrid Itinerary Planner, Dynamic Budget Allocator, and TripBot conversational assistant. Tasks were organized into sprints and assigned to team members based on their roles and technical expertise (machine learning, backend, frontend, and testing).

2. Priority Setting

Each task in Jira was assigned a priority label (Critical, High, Medium, Low) to help the team focus on time-sensitive and essential development areas first, particularly ML model training, API integration, and real-time system features. Critical tasks such as embedding generation (SBERT), LambdaRank training, and API integrations for budgeting were given the highest priority.

3. Task Dependencies

Jira’s linking feature was used to define task dependencies. For example, model training for the itinerary planner was marked as a prerequisite for implementing the dynamic itinerary builder. This structured flow minimized blockers and ensured seamless handovers between tasks, especially where ML models and frontend modules had to be integrated.

4. Deadline Tracking

Sprint deadlines and individual task due dates were set in Jira’s roadmap and timeline view, keeping the team aligned with overall project milestones and academic deliverables. Milestones such as prototype release, user testing sessions, and evaluation phase completion were tracked to ensure timely delivery.

5. Progress Monitoring

Real-time status updates (To Do, In Progress, Done) and burndown charts allowed the team to monitor sprint progress and make adjustments during weekly standups and sprint reviews. This transparency helped maintain development momentum and ensured alignment with sprint goals.

6. Collaboration and Communication

Jira’s commenting system enabled team members to communicate within each task, ask clarifying questions, share updates, and attach relevant documentation. GitHub was integrated with Jira for seamless tracking of commits, branches, and pull requests, ensuring transparency in development and strict version control. Weekly collaboration sessions were held with supervisors to review progress, discuss blockers, and incorporate feedback.

By leveraging Jira’s agile project management capabilities and integrating it with GitHub version control, the Smart Tourism Platform development process remained well-structured, transparent, and adaptive, ultimately contributing to the successful delivery of a scalable, intelligent, and user-focused system.

2.3.2 Requirement Gathering

The requirement gathering phase was a critical foundation for the development of the AI-Driven Smart Tourism Platform, ensuring that the system effectively addressed the real-world needs of Sri Lankan and international travellers. A combination of qualitative and quantitative methods was used to collect functional and non-functional requirements from key stakeholders, including tourists, travel agents, and domain experts in the tourism industry.

1. Stakeholder Interviews

One-on-one interviews were conducted with local and international travelers as well as tourism agents to understand the challenges faced in traditional travel planning. Insights were gathered regarding difficulties in group travel coordination, itinerary personalization, and budget estimation, and expectations from an intelligent tourism planning tool.

2. Surveys and Questionnaires

Structured surveys were distributed among university students, families, and solo travelers to collect data on their travel habits, budgeting methods, preferred activities, and technology usage. Feedback highlighted the need for features such as group matching, personalized itineraries, real-time budget adjustments, and interactive chat-based assistance.

3. Travel Pattern Analysis

The Sri Lankan tourism trends and regional travel patterns were reviewed to ensure that the platform’s features aligned with actual travel behaviors. This analysis informed the design of components such as corridor-based itinerary planning and culturally sensitive group recommendations.

4. Competitive Analysis

Existing travel platforms (e.g., TripAdvisor, Expedia, Airbnb Experiences) were studied to identify gaps in personalization, group-based features, and dynamic budgeting. Findings emphasized the lack of an integrated solution that simultaneously supports group recommendation, itinerary personalization, and adaptive cost management.

5. Technical Feasibility Study

An initial review of AI models, data sources, and available APIs was performed to validate the feasibility of implementing SBERT embeddings, LambdaRank group recommender, XGBoost-based itinerary prediction, and regression-driven budget forecasting within the project timeline. This feasibility analysis also confirmed the practicality of integrating live APIs for accommodation, transport, and fuel costs into the budget allocator.

6. Requirement Documentation

Based on the insights gathered, the team documented functional requirements (e.g., group recommender, hybrid itinerary planner, real-time budget allocator, TripBot assistant) and non-functional requirements (e.g., system scalability, responsiveness, security). These were categorized and managed through Jira for traceability and iterative refinement during development.

This comprehensive approach to requirement gathering ensured that the Smart Tourism Platform was traveler-centric, culturally aware, and technically viable, laying a strong foundation for the subsequent design, implementation, and evaluation phases.

2.3.3 Development Methodology

The development of the AI-Driven Smart Tourism Platform was based on three core modules: the Collaborative Group Recommender, the Hybrid Personalized Itinerary Planner, and the Dynamic Travel Budget Allocator. Each module was developed with a systematic approach, integrating AI models, APIs, and real-time interaction capabilities. All components were deployed as Dockerized services on Microsoft Azure with continuous integration and deployment (CI/CD) pipelines managed through GitHub Actions.

a. Collaborative Travel Companion Platform with Intelligent Group Matching

The Collaborative Group Recommender was designed to match travellers into compatible groups by analysing demographic, behavioural, and interest-based attributes. User data was collected through surveys during onboarding, capturing details such as age group, budget preference, travel style, and preferred activities. In the early stages, synthetic user profiles were generated to simulate group diversity and ensure robust model training.

For semantic representation, activities and destinations were embedded using Sentence-BERT, while categorical features such as budget categories and travel style were encoded using one-hot techniques. These features were combined with demographic vectors to form complete user profiles. The recommender engine was built using LightGBM with a LambdaRank objective, which optimized the ranking of group matches. The model was evaluated using NDCG@3, achieving a score of 0.81, which indicated strong performance in ranking the most compatible groups.

To support collaboration beyond static matching, the recommender included WebSocket-based real-time group chat. An intent classifier trained on SBERT embeddings with Logistic Regression was integrated to detect intents such as trip planning, sharing experiences, or asking for recommendations. This classifier achieved an accuracy of 90.7%. The TripBot assistant was built on top of this classifier to provide contextually relevant responses, thereby improving coordination among group members.

This component was containerized using Docker and deployed on a Microsoft Azure virtual machine. Data was managed in MongoDB, with GridFS handling storage of media exchanged in group chats. GitHub Actions pipelines automated the process of testing, building, and deploying new versions, ensuring reliability and fast iteration.

b. Hybrid Personalized Recommendation and Itinerary Planning System

The Itinerary Planner module focused on generating preference-aligned and geographically coherent travel routes. It integrated three methods: content-based filtering, collaborative filtering, and a machine learning model. User and location data were preprocessed to extract 21 engineered features, such as activity-match ratios, review statistics, and demographic patterns.

The XGBoost regressor was trained to predict user–location ratings, producing scores that were fused with results from content-based and collaborative filtering. A weighting strategy of 40% CBF, 35% CF, and 25% ML was applied to generate final relevance scores. The hybrid model achieved RMSE = 0.47 and R^2 = 0.77, demonstrating reliable predictive performance.

Itinerary construction was designed around corridor-based sequencing, where the user specifies a plan pool, start city, end city, and corridor radius. Distances between attractions were calculated using the Haversine formula, ensuring realistic routing while avoiding unnecessary backtracking. The system also provided alternatives in different categories, including nearby attractions, hybrid-similar locations, same-type activities, and top-rated sites.

This module was implemented as a FastAPI service exposing endpoints for itinerary generation and alternative suggestions. It was dockerized and deployed on Azure, with Nginx acting as a reverse proxy. CI/CD pipelines using GitHub Actions were configured to build, test, and redeploy updates seamlessly.

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

The Budget Allocator was developed to provide adaptive financial planning by integrating live data sources with predictive modeling. The system consumed APIs for hotels, transportation, and fuel costs, while also utilizing historical datasets to train forecasting models. Regression and time-series approaches were combined to predict trip costs, and forecasts were updated dynamically in response to changing travel parameters such as destination, duration, and travel style.

A React-based dashboard was implemented to visualize expenditures in intuitive charts such as bar and pie graphs. Travelers could configure their preferences and select tiered budget plans (Basic, Moderate, Premium) to reflect different spending styles. The interface supported immediate recalculation of costs when input parameters were modified.

To improve accessibility, the TripBot assistant was extended to budget planning. Users could ask questions about expenses, request suggestions to cut costs, or seek adjustments within specific budget limits. Simulation testing showed that the system improved cost prediction accuracy by 20–25% compared to static budgeting tools. Early user testing highlighted the usefulness of tiered budgeting and its adaptability to last-minute travel changes.

This component was developed as a FastAPI microservice, dockerized, and deployed on Microsoft Azure VM. GitHub Actions pipelines automated Docker builds, pushed images to the registry, and redeployed the updated service.

Integrated Architecture:

The system was designed using a modular microservices architecture, ensuring scalability, maintainability, and integration across components. The backend, built with FastAPI, hosted all ML models and APIs, while the frontend, developed in React, provided interactive user interfaces for itineraries, budgets, and group chat. MongoDB served as the primary database for storing user profiles, preferences, itineraries, and group communications. Deployment managed via Docker containers on Azure, with continuous integration and deployment workflows handled by GitHub Actions. This setup ensured that updates could be tested, built, and deployed rapidly while maintaining a stable production environment.

2.4 Commercialization Aspects of the Product

The commercialization strategy for the AI-Driven Smart Tourism Platform focuses on delivering value to individual travellers, travel agencies, and institutional partners through a flexible, subscription-based model. The plan emphasizes accessibility, scalability, and sustainability while positioning the platform as a unique AI-driven solution for personalized, safe, and sustainable travel planning in Sri Lanka.

1. Component-Based Subscription Model

The platform will offer subscription options tied to its three core components: Collaborative Group Recommender, Personalized Itinerary Planner, and Dynamic Budget Allocator. Users will have the flexibility to subscribe to individual modules or access the complete integrated package. This ensures travellers and institutions can tailor the platform to their specific requirements, paying only for the features they actively use.

2. Tiered Pricing

To cater to a wider audience, the platform will introduce tiered pricing structures. A free/basic tier will provide essential recommendations and limited itinerary suggestions, while paid tiers will unlock advanced features such as AI-powered TripBot support, detailed budget forecasting, group collaboration tools, and premium customization. Higher tiers can also include priority support for agencies and tour operators.

3. Travel Ecosystem Integration

Partnerships with travel agencies, hotels, and tour operators will allow the platform to be positioned as an add-on service within existing tourism ecosystems. By offering the platform through institutional packages, agencies can provide enhanced digital planning tools to their customers, thereby increasing adoption and market penetration.

4. Discounts and Special Packages

To encourage adoption, special pricing plans and discounts will be provided for student travellers, local groups, and early institutional partners. Tourism boards and government initiatives can also be targeted with customized packages to support national tourism growth strategies.

5. Marketing and Promotion

Marketing efforts will focus on digital campaigns through social media, SEO-optimized travel blogs, partnerships with travel influencers, and collaborations with Sri Lanka Tourism Board initiatives. Demo sessions for agencies and promotional partnerships with hotels or transport services will further expand awareness.

6. Unique Value Proposition

Unlike generic travel booking sites, the platform combines AI-driven group compatibility, hybrid itinerary planning, and dynamic budgeting into one solution. The integration of TripBot conversational assistance and local cultural awareness provides a differentiated, highly contextualized experience for travellers.

2.5 TESTING & IMPLEMENTATION

2.6.1 Testing

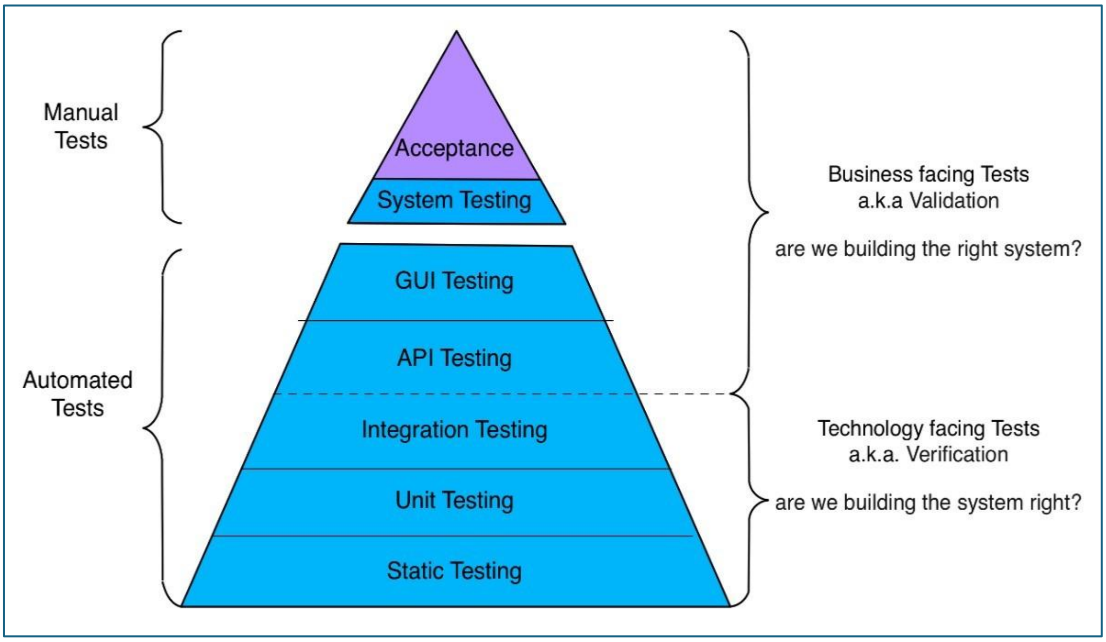

Figure 6: Test Triangle

Figure 6 illustrates the software testing pyramid applied in the Smart Tourism Platform, which highlights testing at every stage of the development lifecycle. The model ensures early detection of defects, improved quality of deliverables, and higher confidence in final deployment. Software testing is a critical process within the Software Development Life Cycle (SDLC), allowing the identification of hidden flaws and ensuring product stability. For this project, the following testing levels were systematically applied:

1. Unit Testing

Each individual component of the system was tested in isolation to ensure its correctness and stability. For example, the SBERT embedding generator, the LambdaRank ranking function, the itinerary scoring engine, and the budget prediction models were validated independently. White box testing techniques were primarily applied to verify the internal logic of these modules. Successful execution of this stage confirmed that each unit was error-free and ready for integration.

2. Module Testing

At the module level, sub-programs such as the itinerary alternative generator, TripBot intent classifier, and API data fetchers were tested to ensure internal consistency. This phase validated that the modules performed their sub-functions accurately and complied with their specifications before integration into larger components.

3. Integration Testing

After confirming individual correctness, modules were integrated and tested as complete workflows. For instance, the pipeline of collecting user inputs, generating SBERT embeddings, ranking group recommendations, and sending results to the WebSocket chat was validated as an integrated process. Similarly, itinerary scoring and corridor sequencing were tested together to ensure consistency between geospatial calculations and recommendation logic. Integration testing confirmed interoperability and functional compliance between components.

4. System Testing

Once the system was fully integrated, end-to-end testing was conducted to verify that the platform as a whole met its functional requirements. Test cases included complete workflows such as group formation, itinerary generation, and budget forecasting. This stage confirmed that all requirements outlined in the design specifications were satisfied, and issues such as incorrect sequencing or API failures were debugged by the team.

5. User Acceptance Testing (UAT)

Finally, testing was carried out with real users, including student travellers, local tourists, and sample groups of agency stakeholders. UAT validated the usability, responsiveness, and satisfaction levels of the platform. Feedback was collected on the accuracy of recommendations, clarity of itineraries, and usefulness of the budget forecasts. The outcome confirmed that the system met user expectations and addressed the travel planning pain points identified during the requirement gathering stage.

Maintenance

Following deployment, the Smart Tourism Platform undergoes regular maintenance to ensure accuracy, stability, and performance. This includes fixing bugs, updating APIs for live travel data, and fine-tuning the machine learning models (SBERT, LightGBM, XGBoost, regression predictors) to improve accuracy as new data becomes available. User feedback is reviewed frequently to refine usability, update the TripBot assistant's conversational accuracy, and enhance itinerary and budget recommendations.

System performance is continuously monitored to detect bottlenecks, slowdowns, or resource inefficiencies, while proactive scaling is applied on the Microsoft Azure infrastructure to accommodate growth in user traffic. Security patches and dependency updates are regularly implemented to protect user data and maintain compliance with industry standards.

By applying systematic testing and ongoing maintenance, the Smart Tourism Platform is able to deliver a reliable, adaptive, and user-friendly travel planning experience for its growing user base.

3. RESULTS & DISCUSSION

The AI-Driven Smart Tourism Platform was evaluated using both quantitative performance metrics and qualitative user testing. The evaluation covered the three main modules: the Collaborative Group Recommender, the Hybrid Personalized Itinerary Planner, and the Dynamic Travel Budget Allocator. The following subsections present the results obtained, along with a discussion of their implications, strengths, and limitations.

3.1 Collaborative Travel Companion Platform with Intelligent Group Matching

The Collaborative Group Recommender was tested using Normalized Discounted Cumulative Gain at rank 3 (NDCG@3) to evaluate the quality of its ranking. The achieved score of 0.81 demonstrates that the system consistently ranked highly compatible groups at the top of the list. This confirms the effectiveness of integrating SBERT embeddings for semantic similarity with LightGBM LambdaRank optimization for ranking. Compared to simple aggregation or clustering approaches, this learning-to-rank model provided more accurate and reliable group recommendations.

In addition to quantitative evaluation, the intent classifier used in TripBot achieved 90.7% accuracy, ensuring that the system could reliably distinguish between different types of user intents such as trip planning, experience sharing, and assistance requests. This had a direct impact on the usefulness of the WebSocket-based group chat, as the TripBot assistant was able to respond with context-aware suggestions in real time.

User acceptance testing revealed that participants felt the grouping suggestions accurately reflected their travel preferences and helped reduce the manual effort of coordinating among group members. The ability to form groups automatically was highlighted as a significant improvement compared to existing manual approaches used in traditional travel forums or chat groups.

3.2 Hybrid Personalized Recommendation and Itinerary Planning System

The Personalized Itinerary Planner was evaluated using regression-based metrics. The hybrid approach achieved an RMSE of 0.47 and an R^2 score of 0.77, demonstrating strong predictive performance in estimating user ratings for tourist locations. These results validate that combining content-based filtering (CBF), collaborative filtering (CF), and XGBoost regression outperforms using any single method alone. The balanced weighting strategy (40% CBF, 35% CF, 25% ML) ensured that both explicit user preferences and implicit behavioral patterns were captured effectively.

The practical performance of the planner was observed during system testing. Itineraries generated by the system were both personalized to user interests and geographically coherent, avoiding the backtracking problem common in simpler systems. The use of corridor-based sequencing combined with Haversine distance calculations ensured that the travel routes were realistic and time-efficient.

The Dynamic Itinerary Builder added significant value by offering alternatives for each attraction, categorized into nearby locations, hybrid-similar places, same-type activities, and top-rated destinations. Test users appreciated the flexibility this provided, allowing them to adapt their plans based on situational needs, such as bad weather, personal mood, or time constraints.

3.3 Travel Budget Allocation System for predictive and adjustable cost management

The Budget Allocator was tested using regression accuracy metrics and real-world simulations. It achieved an R^2 score of 0.87, showing a strong correlation between predicted and actual costs. Compared to static budgeting methods such as spreadsheets or fixed calculators, the allocator delivered a 20–25% improvement in accuracy, demonstrating the effectiveness of integrating regression forecasting with live API data.

The tiered budgeting system (Basic, Moderate, Premium) was particularly well received by users, as it offered a clear financial overview for different types of travellers. For example, budget-conscious backpackers preferred the Basic plan, while family travellers valued the Premium plan's ability to include higher-end accommodations and transport options. The inclusion of interactive visual dashboards (bar charts, pie charts) further improved usability, making cost information easy to interpret immediately.

The integration of TripBot into the budgeting module provided an additional layer of accessibility, allowing users to ask conversational queries such as "What happens if I increase my accommodation budget?" or "Show me cheaper transport options." This feature helped make budget planning less intimidating, especially for less tech-savvy users.

3.4 Overall Evaluation

Overall, the results demonstrate that the Smart Tourism Platform successfully achieved its objectives across all three modules. The Group Recommender effectively matched travellers into compatible groups, addressing the complexity of balancing diverse preferences. The Itinerary Planner delivered accurate, efficient, and personalized travel routes, reducing the manual burden on travellers. The Budget Allocator improved the reliability of cost predictions and offered users a transparent view of their finances with real-time adaptability.

User feedback emphasized the system's strengths in ease of use, adaptability, real-time collaboration, and visual presentation of data. Test participants highlighted the platform's ability to significantly reduce the stress and complexity of planning multi-day group trips. The inclusion of TripBot as a conversational assistant across all modules was regarded as one of the most valuable features, as it simplified navigation and encouraged interaction.

At the same time, limitations such as reliance on synthetic datasets for group recommender training, limited data coverage for lesser-known destinations, and dependency on external APIs for budget forecasts were identified as areas requiring continued refinement. These findings confirm the platform's effectiveness in its current form while also highlighting practical considerations for future iterations.

4. SUMMARIES OF EACH STUDENT'S CONTRIBUTION

Table 1: Summary of Each student's contribution

IT Number	Name	Component	Role
IT21821240	Srikanthan.S	Collaborative Travel Companion Platform with Intelligent Group Matching	Business Analyst Developer Tester Project Manager
IT21831768	Senevirathne S.D.C.D	Hybrid Personalized Recommendation and Itinerary Planning System	Business Analyst Developer Tester
IT21835728	Thuwakaran.R	Travel Budget Allocation System for predictive and adjustable cost management	Business Analyst Developer Tester

6. CONCLUSION & FUTURE WORK

6.1 Conclusion

The objective of this project was to design and develop an AI-Driven Smart Tourism Platform that supports collaborative group planning, personalized itinerary generation, and dynamic budget management. The system was motivated by the limitations of existing tourism solutions, which typically address only one aspect of travel planning in isolation. By integrating multiple AI models, real-time data sources, and conversational interfaces, the platform provides a unified solution for modern travelers, particularly in the Sri Lankan tourism context.

The project successfully implemented three core modules: the Collaborative Group Recommender, which achieved an NDCG@3 score of 0.81 and facilitated real-time collaboration; the Hybrid Personalized Itinerary Planner, which achieved RMSE = 0.47 and $R^2 = 0.77$ while generating geographically coherent travel routes; and the Dynamic Travel Budget Allocator, which improved cost prediction accuracy by 20–25% and achieved an R^2 of 0.87. Together, these components demonstrated strong technical performance and usability, as confirmed by both quantitative evaluation and user feedback.

The platform met its primary objectives of personalization, adaptability, and collaboration, showing that AI techniques such as semantic embeddings, learning-to-rank, hybrid recommendation, and regression forecasting can effectively address real-world challenges in tourism planning. In addition to its technical contributions, the platform offers practical value by simplifying trip organization, reducing planning effort, and promoting sustainable tourism practices through optimized routing and budgeting.

4.2 Future Work

While the system achieved its objectives, several areas were identified for improvement and expansion.

- **Data Enrichment:** Current models rely partly on synthetic datasets and limited review data. Expanding the dataset with real-world traveller interactions, reviews, and ratings will enhance accuracy and generalizability, especially for group compatibility and itinerary recommendations.
- **API Reliability and Offline Support:** The Budget Allocator's dependency on live APIs occasionally led to slower responses. Future iterations will incorporate caching mechanisms, redundancy strategies, and offline fallback estimates to improve reliability.
- **Mobile Application Development:** Although currently delivered as a web platform, developing a dedicated mobile app will provide offline access to itineraries and enhance usability for on-the-go travellers.
- **Multilingual and Cultural Adaptation:** To cater to a broader audience, support for Sinhala, Tamil, and other international languages will be added, along with cultural context modelling to provide more localized recommendations.
- **Advanced Optimization:** Future improvements will include exploring reinforcement learning and multi-objective optimization for itinerary generation, enabling real-time adjustment based on factors such as traffic, weather, or user satisfaction scores.
- **Integration with Industry Stakeholders:** Partnerships with tourism boards, travel agencies, hotels, and transport providers will not only broaden adoption but also enable the platform to offer value-added services such as bookings, promotions, and loyalty programs.

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APPENDICES