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

(TRAVEL BUDGET ALLOCATION SYSTEM FOR PREDICTIVE AND ADJUSTABLE COST MANAGEMENT)

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DECLARATION

I declare that this is my 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 my 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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The above candidate has carried out this research thesis for the Degree of Bachelor of Science (honors) Information Technology (Specializing in Software Engineering) under my supervision.

-------------------------------------- 29/08/2025

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Date

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Signature of co-supervisor

(Ms. Karthiga Rajendran)

Date

ABSTRACT

Travel budgeting is a critical aspect of modern trip planning, yet traditional tools often remain static and unable to adapt to fluctuating market conditions, evolving traveler preferences, or unexpected changes in itineraries. This research presents an AI-powered Travel Budget Allocation System, developed as a core module within a smart tourism platform, to deliver dynamic, accurate, and user-centric financial planning support.

The system integrates three key components: a Data Layer that aggregates historical datasets and live pricing through APIs; a Prediction Engine employing machine learning models such as regression and time-series forecasting for cost estimation; and a User Interface Layer that enables travelers to configure preferences and view results through interactive dashboards. Development followed a structured process of data collection, algorithm design, interface development, and iterative testing.

Experimental evaluation demonstrates a significant improvement in budget prediction accuracy, with simulations showing a 20–25% increase in precision compared to conventional tools. Forecast updates were generated in under two seconds, ensuring responsiveness across diverse scenarios. Early user testing further confirmed the effectiveness of tiered budget options (Basic, Moderate, Premium) and visualized cost breakdowns in enhancing decision-making and financial confidence.

By addressing critical limitations of existing solutions, this system contributes a novel, adaptable, and data-driven approach to travel expense management. It not only empowers individual travelers with transparent and customizable budget control but also offers strong potential for commercialization within the tourism industry, including applications for travel agencies and corporate travel planning.

Keywords – *Travel Budget Allocation, Predictive Analytics, Real-Time Forecasting, Personalized Recommendations, Smart Tourism, Cost Optimization.*

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LIST OF ABBREVIATIONS

Abbreviation	Description
AI	Artificial Intelligence
APIs	Application Programming Interfaces
ML	Machine Learning
VS Code	Visual Studio Code
UI	User Interface
AWS	Amazon Web Services
NoSQL	"Not Only SQL" (non-relational database model)
GCP	Google Cloud Platform
GPU	Graphics Processing Unit
IDE	Integrated Development Environment
TBAS	Travel Budget Allocation System
MAE	Mean Absolute Error

B2B	Business-to-Business
B2G	Business-to-Government
SaaS	Software as a Service
B2C	Business-to-Consumer
RMSE	Root Mean Squared Error
LKR	Sri Lankan Rupee

1 INTRODUCTION

1.1 Background and Literature Survey

Travel budgeting is a fundamental element of effective trip planning, regardless of whether the purpose is personal leisure, business, or academic travel. The primary challenge lies in the allocation of financial resources across diverse categories such as transportation, accommodation, meals, and activities, while ensuring both affordability and quality of experience. In recent years, travelers have increasingly sought automated and intelligent solutions to streamline this process. However, most existing tools remain limited in functionality, relying on static templates or manual calculations that fail to adapt to changing circumstances.

Traditional budgeting mechanisms, including simple calculators and spreadsheet-based models, are inherently inflexible. They do not incorporate real-time variables such as airfare fluctuations, seasonal accommodation price shifts, or sudden changes in availability triggered by local events [1]. For example, a traveler may encounter unexpected price surges in flights or last-minute cancellations in hotels, situations where static systems cannot provide timely or accurate adjustments. Furthermore, these tools often present generalized budget recommendations that overlook the nuances of individual traveler preferences, spending patterns, or constraints [2]. This one-size-fits-all approach reduces their effectiveness, particularly in scenarios that demand personalization and adaptability.

Addressing these limitations requires a new generation of budgeting systems capable of integrating real-time data streams, predictive analytics, and adaptive algorithms. Recent advancements in artificial intelligence and data science, particularly in machine learning and time-series forecasting, have created opportunities to overcome the shortcomings of conventional tools. Predictive models can analyze historical data alongside live market inputs, producing accurate forecasts of travel expenses under varying conditions. Similarly, real-time API integration enables systems to access continuously updated information on transportation, accommodation, and related services. Together, these technologies represent a decisive shift from static budgeting to a dynamic, data- driven, and user-centric approach that adapts seamlessly to changing contexts and personal requirements [3].

Such innovations underscore the importance of designing intelligent budget allocation systems that not only enhance financial planning accuracy but also improve traveler confidence and decision-making efficiency.

Gaps in Existing Solutions

Although several digital tools and applications have emerged to support travel budgeting, they continue to suffer from significant limitations that restrict their effectiveness in practical scenarios. These shortcomings can be summarized as follows:

- **Static Data Usage –** Many budgeting tools rely heavily on pre-defined or fixed datasets. This dependence prevents them from capturing the inherently dynamic nature of travel expenses, such as fluctuating airfares, seasonal accommodation rates, or currency exchange variations. As a result, travelers are often left with outdated or inaccurate budget estimates.

- **Limited Personalization –** Most existing solutions are built around generic algorithms and provide standardized recommendations. They do not adequately reflect individual travel styles, preferences, or constraints, such as budget sensitivity, preferred accommodation types, or activity-specific spending priorities [4]. This lack of personalization undermines user engagement and reduces trust in the recommendations provided.

- **Lack of Predictive Analytics –** Only a few current tools attempt to forecast future expenses using predictive algorithms. Without the ability to model cost fluctuations based on historical data, seasonal patterns, or emerging trends, these systems remain reactive rather than proactive in helping users prepare for potential financial changes.

- **Absence of Real-Time Adaptation –** A critical weakness of most tools is their inability to integrate real-time updates. They often fail to respond to live changes in the travel ecosystem, such as sudden price surges, last-minute discounts, or unexpected availability shifts in transportation and accommodation [5]. This absence of dynamic adaptation leads to suboptimal decision-making and missed opportunities for cost savings.

Collectively, these gaps highlight the need for an intelligent, adaptive, and user-centric travel budgeting system that integrates predictive analytics, real-time data feeds, and personal recommendation mechanisms. Addressing these shortcomings forms the foundation of the proposed AI-powered Travel Budget Allocation System.

Technological Advances in Travel Budgeting

Recent advancements in machine learning, predictive analytics, and real-time data integration have opened new possibilities for addressing the persistent limitations of conventional travel budgeting tools. Predictive algorithms are increasingly capable of analyzing large volumes of historical data and producing reliable forecasts of future travel expenses. By recognizing seasonal patterns, market trends, and user behaviors, these models can generate cost estimations that are significantly more accurate than those derived from static methods.

Equally important is the role of real-time data integration, which ensures that travelers are provided with the most up-to-date pricing information for flights, accommodations, and related services. This capability enables dynamic adjustments to budget recommendations in response to fluctuations such as sudden airfare increases or temporary discounts on lodging [6].

Scholarly work reinforces the importance of these technologies. For example, Smith et al. (2021) demonstrated that incorporating machine learning into budgeting systems can substantially reduce errors in financial forecasting, improving the reliability of budget estimates [7]. Similarly, Johnson (2022) emphasized the value of dynamic algorithms that adapt continuously to market variability, arguing that adaptability is essential for effective financial planning in highly volatile domains such as tourism [8].

Together, these technological advances establish the foundation for next-generation travel budgeting systems, where predictive models, adaptive algorithms, and real-time data streams converge to deliver more accurate, flexible, and user-centered financial planning tools.

Objectives of the Proposed System

The proposed Travel Budget Allocation System is designed to directly address the shortcomings of existing travel budgeting tools by combining predictive analytics, real-time data integration, and user-centric design principles into a unified platform. Unlike conventional approaches, the system provides a personalized, adaptive, and intelligent budgeting experience that evolves dynamically with both market fluctuations and user preferences.

At its core, the system integrates real-time data sources through reliable APIs, enabling continuous updates on transportation, accommodation, meals, and activities. This ensures that travelers receive accurate, timely, and context-specific budget recommendations rather than static, outdated estimates. Complementing this, predictive models powered by machine learning are employed to forecast future expenditures by analyzing historical cost patterns, seasonal pricing trends, and individual user behavior. These algorithms allow the system not only to reflect present conditions but also to anticipate potential changes in expenses, providing a proactive approach to travel budgeting.

The platform further emphasizes usability and personalization through a highly interactive interface. Users can configure key preferences such as overall budget, travel style, destinations, and activity choices, while also tailoring allocations for accommodation, transportation, and other categories. Visual dashboards and adaptive filters enhance engagement, improving both clarity and decision-making confidence.

Finally, the system delivers dynamic recommendations that adjust in real-time to shifts in market conditions or changes in user input. For instance, it can recalibrate budget allocations when airfare prices surge, when travelers switch accommodation preferences, or when itinerary dates are modified. In doing so, the proposed system ensures that users maintain financial control while experiencing flexibility and convenience in their planning process. By integrating these advanced features, the Travel Budget Allocation System represents a next-generation solution that enhances accuracy, improves user experience, and ultimately transforms the way modern travelers manage their financial planning.

Key Questions Explored

To frame the scope of this research and to ensure alignment with the identified gaps in existing solutions, the study is guided by the following key questions:

1. **What are the limitations of current travel budgeting tools?** This question seeks to identify the shortcomings of traditional approaches, particularly their reliance on static data, limited personalization, and lack of real-time responsiveness.

2. **How can predictive algorithms and real-time data integration improve the accuracy and reliability of travel budgeting?**

   Here, the focus is on exploring the contribution of machine learning and live data feeds in producing more precise and adaptive cost forecasts.

3. **How can user-centric design principles enhance accessibility, usability, and overall traveler confidence?**

   This question addresses the importance of intuitive interfaces and interactive features that allow users to customize preferences, visualize costs, and engage meaningfully with the system.

4. **In what ways does the proposed Travel Budget Allocation System overcome these limitations and differentiate itself from existing solutions?**

   This final question ties together the research by evaluating how the proposed system integrates predictive analytics, real-time data, and adaptive interfaces into a cohesive and innovative platform.

Anticipated Benefits

The proposed Travel Budget Allocation System is expected to deliver a range of benefits that collectively transform the travel planning process into a more efficient, accurate, and user-friendly experience.

- First, the system significantly improves efficiency by automating complex budgeting tasks that would otherwise require manual calculations and repeated adjustments. This not only reduces the time and effort spent by travelers but also minimizes the risk of human error in financial planning.

- Second, it enhances accuracy and reliability through the integration of real-time data and predictive analytics. By continuously updating cost estimates across categories such as transportation, accommodation, and activities, the system ensures that users receive precise and up-to-date recommendations that align with both market fluctuations and individual preferences [9].

- Third, the platform supports better decision-making by providing travelers with data- driven insights and transparent visualizations of their financial allocations. These features enable users to evaluate trade-offs, adjust spending priorities, and optimize budgets with greater confidence.

- Finally, the system enhances accessibility and inclusiveness by incorporating a user- friendly, interactive interface. Its intuitive design ensures that travelers with varying levels of technological literacy can engage with the platform effectively. In doing so, the solution broadens its appeal, extending usability across diverse user groups.

Collectively, these benefits demonstrate the system's potential not only to improve the individual travel experience but also to support wider commercialization opportunities, including adoption by travel agencies, corporate travel departments, and digital tourism platforms.

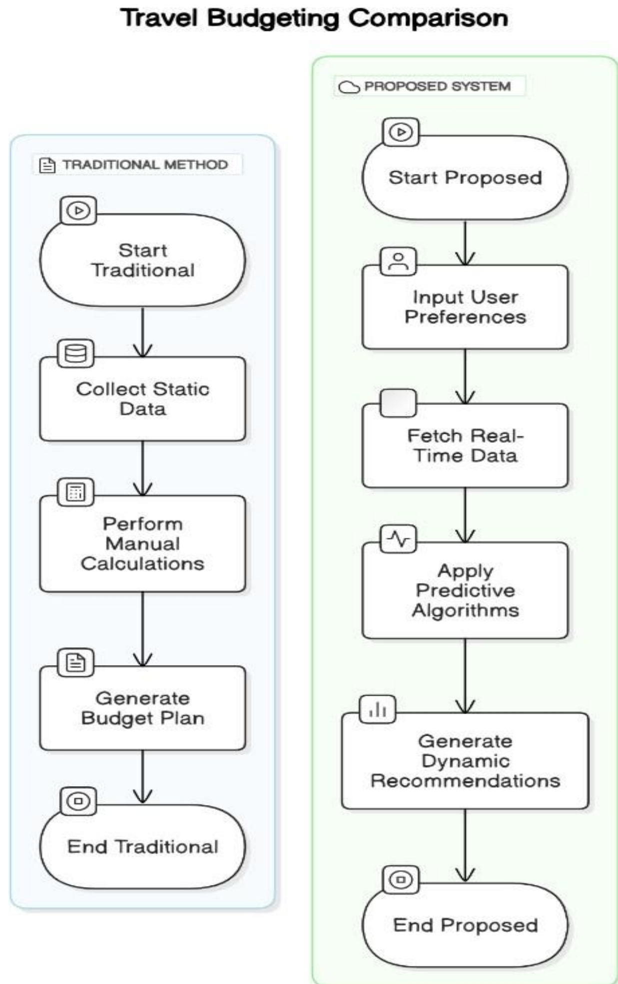

Figure 1-Travel Budgeting Comparison

Relevant Studies

A few prior studies have investigated the limitations of existing travel budgeting tools and highlighted key directions for improvement.

- **Limitations in Static Budgeting Models** – Anderson et al. (2020) examined static budgeting models widely used in conventional travel planning tools. Their findings revealed that such models fail to capture the variability of travel expenses, particularly in the face of sudden price hikes, currency fluctuations, and seasonal anomalies. The study concluded that dynamic systems capable of integrating both real-time data and historical trends are necessary to provide more reliable and adaptable budgeting solutions [1].

- **Role of Real-Time Data in Budget Predictions** – Tan et al. (2021) investigated the impact of incorporating live data into budgeting systems. Their research demonstrated that the use of APIs to retrieve up-to-date pricing and availability significantly improved the accuracy of budget allocations. More importantly, the ability to make real-time adjustments enhanced the responsiveness of such systems, allowing travelers to adapt to rapidly changing conditions with greater financial control [2].

- **Importance of User-Centric Designs** – Zhang et al. (2022) emphasized the critical role of user-centric design in determining the success of budgeting tools. Their study highlighted that intuitive, customizable interfaces not only increase user engagement but also improve accessibility for a wider audience. Features such as interactive visualizations, real-time filters, and immediate feedback mechanisms were found to empower users to manage their budgets more effectively and confidently [3].

Together, these studies reinforce the need for a comprehensive solution that combines dynamic adaptability, real-time data integration, and user-centered design. The proposed Travel Budget Allocation System builds upon these insights by unifying all three elements into a single intelligent platform, thereby addressing the shortcomings identified in earlier research.

Technological Insights

The review of prior studies highlights several technological advancements that provide a strong foundation for enhancing modern travel budgeting systems:

1. **Algorithms for Accurate Cost Prediction** – Advances in machine learning, particularly in regression analysis and time-series forecasting, have proven highly effective in modeling financial data. By analyzing historical travel expenses and seasonal variations, these algorithms can produce precise forecasts of future costs. This predictive capability reduces uncertainty and helps travelers plan with greater confidence.

2. **Integration of Real-Time APIs** – Application Programming Interfaces (APIs) have emerged as a key enabler of real-time financial planning. By providing live updates on flights, accommodations, and other travel components, APIs ensure that budgeting tools can adapt dynamically to fluctuating market conditions. Such integration not only improves the reliability of cost estimations but also allows users to make timely adjustments to their plans [4].

3. **Enhanced Visualization and Usability** – User experience plays a critical role in the success of budgeting platforms. Recent developments in interactive data visualization, such as spending dashboards, charts, and category-based breakdowns, improve the clarity with which users understand their financial allocations. Combined with responsive user interfaces that operate seamlessly across devices, these features significantly increase accessibility and engagement, ensuring that budgeting tools cater to diverse user groups [5].

Collectively, these insights demonstrate that the convergence of predictive algorithms, real-time integration, and user-centric design is essential for developing effective and intelligent travel budgeting systems. These technological directions form the backbone of the proposed Travel Budget Allocation System.

Table 1-Traditional Budgeting Tools vs. Proposed System

Feature	Traditional Tools	Proposed System
Data Type	Static, fixed data	Real-time dynamic data integration
Personalization	One-size-fits-all approach	Personalized recommendations based on user preferences
Adaptability	No real-time adjustments	Dynamic adjustments based on live data
Accuracy	Estimation based on historical data	Accurate forecasting with predictive analytics
User Experience	Basic templates, manual inputs	Interactive interface with customizable features

1.2 Research Gap

Despite the availability of many digital tools aimed at supporting travel budgeting, the majority remain limited in scope and fail to address the practical challenges faced by modern travelers. Most existing systems rely heavily on static and predefined datasets, which restricts their ability to reflect the dynamic nature of travel expenses. For example, airfare prices can fluctuate significantly within hours, accommodation rates can surge due to seasonal demand or local events, and unforeseen circumstances such as cancellations or disruptions can have a direct impact on total costs. Since traditional systems are unable to capture these fluctuations, travelers are often presented with outdated or misleading estimates.

In addition, current solutions frequently offer generalized and one-size-fits-all recommendations. These ignore the wide diversity in traveler preferences, financial constraints, and travel styles, such as luxury versus budget-conscious approaches. As a result, users may find that the allocations provided do not align with their actual needs, leading to suboptimal financial planning and overspending. A further limitation is the absence of predictive analytics, which would allow systems to anticipate future cost changes by analyzing historical data, seasonal pricing trends, and user behaviors. Without this capability, current tools remain reactive, providing estimates based only on present conditions rather than forecasting upcoming variations.
The core research gap therefore lies in the absence of integrated systems that combine three essential capabilities

- **Real-time data integration** – ensuring cost estimates remain current and context-specific by drawing on live updates from transportation, accommodation, and related services.

- **Predictive algorithms** – employing machine learning models such as regression analysis and time-series forecasting to anticipate travel cost variations with greater accuracy.

- **User-centric design** – enabling personalized recommendations that consider individual travel styles, budgetary constraints, and destination-specific factors.

The proposed research aims to bridge this gap by developing an AI-powered Travel Budget Allocation System that unites these capabilities into a single adaptive platform.

By incorporating predictive models, real-time pricing data, and interactive user interfaces, the system will provide travelers with accurate, personalized, and dynamic budget recommendations. This will not only enhance financial transparency and confidence in decision-making but will also deliver a more efficient and user-friendly budgeting experience. Ultimately, such a system has the potential to optimize travel expenditure management while aligning with the growing demand for intelligent, data-driven solutions in tourism planning.

Table 2-Gaps in Current Travel Budgeting Systems

Current System Limitation	Description
Static Budgeting	Relies on fixed data, leading to inaccuracies in forecasting.
Limited Real-Time Data	Fails to adjust to real-time fluctuations in prices.
Generic Recommendations	One-size-fits-all approach, not tailored to individual preferences.
Lack of Adaptability	No automatic adjustments based on changing parameters.

1.3 Research Problem

Travel planning continues to pose significant challenges for individuals and organizations, largely due to the limitations of current travel budgeting tools. Many existing systems adopt a one-size- fits-all approach, which disregards the diversity of traveler needs, preferences, and contexts. As a result, they are often ineffective for users with unique requirements or for those whose plans evolve dynamically during a trip.

A key weakness of conventional tools is their inability to account for real-time cost fluctuations. Travelers frequently encounter last-minute deals, sudden price surges, or unexpected changes in transportation and accommodation availability. Without mechanisms to adapt to these variations, existing systems provide outdated or misleading recommendations that compromise financial accuracy. In addition, most tools lack the ability to incorporate individual preferences, such as preferred travel styles, budget sensitivity, or specific accommodation choices. This absence of personalization frequently results in inefficient budget allocation and unnecessary overspending.

The core research problem therefore lies in the absence of a comprehensive and adaptive travel budgeting system that is capable of:

- Integrating real-time cost data from multiple sources
- Leveraging predictive analytics for accurate financial forecasting
- Delivering personalized recommendations tailored to user-specific preferences.

In the absence of such capabilities, travelers face recurring difficulties in adhering to their budgets and struggle to make timely adjustments when unforeseen circumstances arise. This lack of flexibility and adaptability contributes to frustration, reduced financial control, and ultimately, suboptimal travel experiences.

To address this challenge, the present research proposes the development of a dynamic, data-driven Travel Budget Allocation System. By combining predictive algorithms, real-time pricing data, and user-centric design, the system aims to provide travelers with better financial control, more accurate and timely budget adjustments, and an overall enhanced planning experience.

1.4 Research Objectives

1.4.1 Main Objective

The primary objective of this project is to design and develop an intelligent Travel Budget Allocation System capable of delivering automated, personalized budget recommendations for travelers. Unlike conventional tools that rely on static calculations, the proposed system will harness real-time data sources such as transportation fares, accommodation rates, seasonal fluctuations, and destination-specific cost indexes. By incorporating user-specific preferences, including travel duration, companion type, lifestyle choices, and spending priorities, the system will provide highly relevant and adaptive recommendations.

A key innovation lies in its ability to dynamically respond to fluctuations in travel costs. Through the application of predictive analytics, machine learning models, and advanced data retrieval techniques, the system will forecast upcoming changes and adjust the budget allocations accordingly. This ensures that users not only receive accurate cost projections but also remain financially prepared for unexpected variations.

Furthermore, the system aims to optimize resource allocation by intelligently distributing expenses across major categories such as transport, accommodation, food, and activities. By offering up-to- date, tailored budget suggestions, travelers will be empowered to make informed financial decisions, minimize overspending risks, and maximize the overall value of their trips. Ultimately, this project envisions a comprehensive platform that not only streamlines the budgeting process but also enhances user confidence and satisfaction in achieving their travel goals within defined financial constraints.

1.4.2 Specific Objectives

- **Implementing Predictive Algorithms for Cost Estimation**

- **Objective:** Develop and integrate predictive models that estimate travel costs using both historical data and real-time inputs. These algorithms will forecast expenses in key travel categories, such as accommodations, meals, and transportation, factoring in seasonal price variations and market trends. The system will continuously update these predictions to ensure that users receive accurate and timely financial insights, with a particular emphasis on road travel costs, including fuel, tolls, vehicle rentals, and other related expenses.
- **Outcome:** Dynamic, accurate cost estimations that adjust to market trends and user preferences, improving the overall budget accuracy.

- **Design a User-Friendly Interface for Customization**

- **Objective:** Create an intuitive, user-centric interface that allows travelers to set and customize their budget preferences, such as preferred travel dates, accommodation types, and expenditure limits for activities. The system will offer customizable filters that accommodate various travel styles (e.g., luxury, budget, adventure), providing a highly personalized experience. The interface will ensure that budget recommendations align with individual traveler goals, simplifying the budgeting process.
- **Outcome:** A seamless and engaging user experience that empowers travelers to manage their budgets and receive tailored, relevant recommendations.

- **Integrate APIs for Real-Time Travel Cost Retrieval**

- **Objective:** Integrate reliable external APIs from sources such as hotel aggregators and transportation services to retrieve real-time travel cost data. This integration will allow the system to adjust budget recommendations based on the latest pricing information for accommodations, road transportation, vehicle rentals, fuel prices, tolls, and other related expenses.
- **Outcome:** Real-time updates that reflect current travel cost data, ensuring that recommendations are both relevant and actionable.

- **Validate the System Through Rigorous Testing and Iterative Refinements**

- **Objective:** Conduct comprehensive testing to validate the performance, accuracy, and usability of the Travel Budget Allocation System. This will involve iterative refinements based on real-world user feedback, including handling edge cases such as price surges or sudden changes in user preferences. Testing will ensure that the system effectively handles complex travel scenarios and provides reliable budget recommendations.

- **Outcome:** A robust and reliable system capable of delivering accurate, actionable recommendations across diverse travel contexts, while adapting to unexpected changes in user plans or market conditions.

1.4.3 Business Objectives

The Travel Budget Allocation System is not only designed to serve individual travelers but also to generate broader business value by addressing gaps in the current travel technology market. The following business objectives will guide the system's strategic direction:

1. Enhance Market Competitiveness in Travel Tech

By offering real-time, predictive budget recommendations that adapt to cost fluctuations, the system differentiates itself from traditional static budgeting tools. This innovation strengthens the organization's positioning in the growing smart-tourism and fintech-enabled travel solutions market.

2. Increase User Adoption and Retention

Through its user-friendly, customizable interface and personalized financial insights, the system aims to attract a wide user base, from budget travelers to luxury seekers. The tailored experience encourages repeat usage, improves customer satisfaction, and builds long-term loyalty.

3. Drive Revenue Opportunities

The integration of external APIs (e.g., hotel aggregators, transportation providers, and rental services) creates opportunities for affiliate partnerships and commissions, transforming the platform into a revenue-generating ecosystem. Additionally, premium features such as advanced analytics, itinerary optimization, and financial tracking can be monetized through subscription models.

4. Optimize Operational Efficiency

By leveraging machine learning and predictive analytics, the system reduces manual intervention in cost estimation and financial planning, ensuring faster, more accurate recommendations. This efficiency allows the business to scale effectively while minimizing operational overhead.

5. Build Trust and Brand Value

Delivering accurate, reliable, and adaptive recommendations enhances traveler confidence in financial planning. A robust validation and testing process ensures consistent performance across varied scenarios, which strengthens trust, boosts brand reputation, and supports expansion into international markets.

6. Support Long-Term Sustainability

By helping travelers manage their budgets efficiently and avoid overspending, the system promotes sustainable financial practices. In addition, the inclusion of sustainability-oriented filters (e.g., eco-friendly accommodations or low-emission transport) provides a future pathway for aligning with global sustainable tourism trends, adding long-term value for both users and stakeholders.

2 METHODOLOGY

2.1 Methodology

The methodology adopted for this project follows a hybrid approach, combining Agile Scrum practices with the seven-stage Software Development Life Cycle (SDLC). This dual framework was chosen to balance adaptability to changing requirements with systematic evaluation of each subsystem of the Travel Budget Allocation System: the Data Collection Layer, Prediction Engine, and User Interface Layer.

- **Agile Scrum Practices**

Development was carried out in short sprints (2–3 weeks), where each sprint focused on a core module such as:

- real-time data collection and API integration
- development of predictive cost models (regression and time-series forecasting)
- design of interactive user dashboards.

Sprint reviews, retrospectives, and daily stand-ups facilitated continuous feedback, iterative improvements, and stakeholder alignment. Tools such as Jira and GitHub Projects were used for backlog management, sprint tracking, and issue resolution.

- Seven-Stage SDLC

Alongside Agile, the structured phases of SDLC guided the overall project lifecycle:

- **Feasibility Study** – assessed technical, financial, and practical viability of integrating real-time APIs and predictive models.

- **Requirements Analysis** – captured functional needs such as personalized budget inputs, predictive accuracy, and real-time updates, as well as non-functional needs like scalability and usability.

- **System Design** – architected the three layers (Data Collection → Prediction Engine → User Interface) ensuring modularity and scalability.

- **Implementation** – built the backend (Python, Node.js, MongoDB), frontend (React), and integrated APIs for travel data.

- **Testing** – conducted unit, integration, system, and user acceptance testing to ensure accuracy, reliability, and responsiveness.

- **Deployment** – deployed the system on a cloud platform (AWS/GCP) for scalability and global accessibility.

- **Maintenance** – included continuous API updates, bug fixes, and iterative enhancements based on user feedback.

The combination of Agile flexibility and SDLC structure enabled the successful integration of real-time APIs, predictive machine learning models, and a scalable front-end-backend system. This ensured that the platform not only met its research objectives but also delivered accurate, user-friendly, and adaptive budgeting experience aligned with traveler needs.

2.1.1 Functional Requirements

The functional requirements define the core capabilities that the Travel Budget Allocation System must deliver to achieve its intended objectives. These requirements ensure that the system provides accurate, dynamic, and user-centric budget recommendations.

1. **Real-Time Data Integration**

- Requirement: The system must integrate seamlessly with external APIs to gather real-time travel-related information, including airfares, hotel rates, vehicle rental costs, and local transportation prices.

- Justification: Travel expenses fluctuate constantly due to factors such as seasonal demand, special events, and market conditions. Without live data, the system would provide outdated or misleading recommendations.

- Expected Outcome: Users will receive up-to-date and contextually relevant budget estimates, enabling them to plan with accuracy and confidence.

2. **Customizable Inputs**

- Requirement: Users should be able to input and modify key variables such as travel destination, dates, accommodation preferences, activity selections, and budgetary limits.

- Justification: Each traveler has unique financial constraints and preferences, which cannot be adequately addressed by a one-size-fits-all budgeting approach. Personalization is therefore essential for practical adoption.

- Expected Outcome: The system will deliver tailored budget recommendations that align with individual traveler goals, thereby enhancing both usability and trust in the platform.

```
# Example usage
locations = ["LOC_11", "LOC_42", "LOC_6"]
package = "Moderate"
total_days = 12
rating_range = "3-5"
travel_companion = "Family"
```

Figure 2-Customizable User Input Model

3. **Accurate Predictions**

- Requirement: The system must provide reliable budget forecasts by leveraging predictive algorithms that analyze historical pricing data while incorporating real-time inputs such as seasonality, currency exchange rates, and sudden market fluctuations.

- Justification: Static cost estimates fail to anticipate upcoming changes, often resulting in overspending or poor allocation of resources. Predictive analytics ensures forward-looking recommendations.

- Expected Outcome: Users will benefit from precise, proactive financial forecasts, allowing them to anticipate potential cost increases or savings opportunities and make informed travel decisions.

```
[6] # Make predictions
    y_pred = xgb_model.predict(X_test)

    # Evaluate the model
    mae = mean_absolute_error(y_test, y_pred)
    rmse = mean_squared_error(y_test, y_pred) ** 0.5
    r2 = r2_score(y_test, y_pred)

    # Display evaluation results
    print(f"✅ XGBoost Model Evaluation:\nMAE: {mae:.2f} LKR\nRMSE: {rmse:.2f} LKR\nR² Score: {r2:.4f}")

✅ XGBoost Model Evaluation:
MAE: 2769.10 LKR
RMSE: 5242.96 LKR
R² Score: 0.9519
```

Figure 3-Prediction Accuracy Calculation

2.1.2 Non-Functional Requirements

In addition to the functional features, the Travel Budget Allocation System must also satisfy several non-functional requirements. These define the quality attributes of the system, ensuring that it performs consistently, efficiently, and is accessible to a broad range of users.

1. **Reliability of Predictions**

- Requirement: The system should ensure that its predictions are consistent and reliable. When the same input parameters are provided, the system must produce the same results unless real-time data has changed.

- Justification: Travelers rely on accurate and repeatable financial insights to make informed decisions. Inconsistent outputs may undermine trust in the system and reduce adoption.

- Expected Outcome: Users will receive stable and dependable recommendations, with variations only reflecting genuine changes in market or pricing data.

2. **Fast Response Times**

- Requirement: The system must deliver budget recommendations with minimal latency, even under high data loads or during the execution of complex prediction queries. Ideally, response times should remain under 2–3 seconds for standard queries.

- Justification: In travel planning, responsiveness is critical. Delays can disrupt decision-making, particularly when users are comparing alternatives or responding to price fluctuations.

- Expected Outcome: A high-performance system that provides users with near-instantaneous recommendations, ensuring smooth interaction and increased satisfaction.

3. **User-Friendly Interface**

- Requirement: The interface must be intuitive and accessible, allowing both novice and experienced users to easily navigate, enter preferences, and access recommendations without unnecessary complexity.

- Justification: Usability is a key factor in adoption. A complicated or poorly designed interface could discourage users from engaging with the system, regardless of its predictive accuracy.

- Expected Outcome: A seamless and engaging user experience, where clear layouts, simple navigation, and effective data visualizations foster traveler confidence and promote wider usage.

2.1.3 User Requirements

The Travel Budget Allocation System is intended to serve a diverse group of travelers with varying needs, preferences, and levels of technical expertise. To ensure its practicality and adoption, the system must satisfy the following user requirements

1. **User Input Flexibility**

- Requirement: Users should have the ability to enter and modify key preferences, including travel destinations, dates, accommodation types, and activity choices. The system must generate budget estimates that respond directly to these inputs.

- Justification: Each traveler's priorities are unique, and budgeting decisions vary widely depending on purpose (e.g., leisure, business, family travel). Rigid systems that do not allow customization often to fail to meet user expectations.

- Expected Benefit: By enabling flexible inputs, the system ensures that recommendations are tailored to individual plans, resulting in greater relevance and user satisfaction.

2. **Personalized Budget Recommendations**

- Requirement: The system must generate budget estimates tailored to individual inputs, reflecting personal constraints such as budget limits, preferred travel style (e.g., budget-friendly or luxury), and desired activity mix. Users should also be able to instantly view updated predictions when modifying preferences.

- Justification: Generic, one-size-fits-all recommendations reduce trust and usability, as they often fail to reflect actual travel behavior. Personalized recommendations create greater alignment between system outputs and user expectations.

- Expected Benefit: Travelers will receive realistic and practical financial guidance, improving both planning efficiency and confidence in budget management.

3. **Real-Time Feedback**

- Requirement: The system must provide immediate, up-to-date cost predictions, with recommendations dynamically adjusting to live changes in market data such as airfare fluctuations, accommodation availability, and seasonal pricing.

- Justification: Travel costs are inherently volatile, and delays in reflecting changes can result in missed opportunities or overspending. Real-time updates are therefore essential for financial accuracy and decision-making.

- Expected Benefit: Users will gain greater financial control and responsiveness, enabling them to adapt plans quickly and optimize spending in alignment with current market conditions.

2.1.4 System Requirements

The development and deployment of the Travel Budget Allocation System requires a set of well- defined software and hardware resources. These requirements ensure that the system is capable of handling large datasets, performing predictive analytics, and delivering a responsive, user-friendly experience.

➢ **Software Requirements**

  - **Python:** Serves as the primary programming language for implementing backend algorithms, machine learning models, and data processing workflows. Python was selected due to its extensive ecosystem of libraries such as Scikit-learn and Pandas, which facilitate predictive analytics, data manipulation, and trend analysis.

  - **React:** Used to develop a responsive and dynamic front-end interface. React enables the creation of interactive dashboards and customizable components, ensuring that users can easily configure preferences and visualize budget recommendations in real time.

  - **Node.js:** Functions as the runtime environment for building the backend server. Node.js supports efficient handling of concurrent API requests, communication with databases, and system scalability, making it well-suited for applications requiring fast response times.

  - **MongoDB:** Provides a flexible and scalable database solution for managing both historical datasets and real-time inputs. As a NoSQL database, MongoDB can handle unstructured and semi-structured data efficiently, ensuring fast retrieval and storage for large-scale travel datasets.

- **External APIs:** Integrated to fetch real-time travel-related data such as airfare prices, hotel rates, fuel costs, and other essential expenses. These APIs ensure that the system remains dynamic and continuously updated, enabling more accurate and context-specific budget predictions.

➢ **Hardware Requirements**

- **Development Environment:** A workstation or computer with sufficient processing power to manage large datasets and run machine learning algorithms efficiently. A minimum of 16 GB RAM, SSD storage, and multi-core processors are recommended.

- **GPU Acceleration:** For algorithm training and predictive analytics, access to a Graphics Processing Unit (GPU) is recommended. GPUs significantly reduces the training time for machine learning models, particularly when processing large historical datasets and performing real-time inference.

- **Servers or Cloud Platforms:** For deployment, scalable infrastructure is required. Cloud platforms such as AWS, Azure, or Google Cloud can provide flexible hosting solutions with on-demand resource allocation. This ensures that the system remains reliable under varying workloads and can support future expansion.

2.1.5 System Overview

The proposed Travel Budget Allocation System is designed as a data-driven and adaptive solution for managing and predicting travel expenses with a high degree of accuracy, reliability, and user-friendliness. The system architecture is organized into three interdependent layers: Data Collection Layer, Prediction Engine, and User Interface Layer. Each layer is designed to perform specific functions while maintaining seamless interaction with the others to ensure smooth and efficient operation.

- ✓ **Data Collection Layer**

The Data Collection Layer forms the foundation of the Travel Budget Allocation System (TBAS). Its primary role is to ensure that all budget forecasts and recommendations are grounded in accurate, timely, and comprehensive data. Since travel expenses are highly volatile and influenced by numerous dynamic factors, this layer is designed to aggregate, preprocess, and validate data from multiple sources, thereby creating a solid and reliable knowledge base for subsequent analysis.

Real-Time Data Integration

To reflect current market conditions, TBAS integrates with multiple Application Programming Interfaces (APIs) provided by travel-related services. These include:

- Airline and airfare engines (e.g., Skyscanner, Amadeus) to capture dynamic fluctuations in flight prices.
- Hotel booking platforms (e.g., Booking.com, Expedia) to provide up-to-date accommodation costs across a range of categories.
- Car rental services and ride-hailing providers to account for local and intercity transport costs.
- Fuel price aggregators and toll databases to estimate expenses related to self-driven or road-trip scenarios.

- Public transportation networks to gather fares for buses, trains, and metro systems in specific cities or regions.

By establishing direct connections with these APIs, the system can update cost information in near real-time. This ensures that travelers receive recommendations that are relevant to the exact conditions at the time of planning, rather than outdated averages. For example, airfare predictions can capture sudden fare surges caused by holiday seasons or flash discounts due to last-minute cancellations.

Historical Data Utilization

In addition to real-time streams, TBAS also incorporates historical travel datasets. These long-term datasets, often spanning several years, allow the system to identify patterns and trends in travel expenses that would otherwise be missed if relying only on current prices. Examples include:

- Seasonal accommodation surges during Christmas and New Year.
- Recurring airfare hikes during summer vacation periods.
- Gradual increases in fuel prices due to inflation or regional supply-demand shifts.

This dual data strategy (real-time + historical) allows the system to balance immediacy with foresight. While real-time data ensures responsiveness to current conditions, historical data provides predictive stability, enabling the system to forecast likely future expenses based on past trends.

5231	LOC_76	PACK_76Z3-1	Premium	Sunrise Visit, Attend Thaipoosam Festival with Private Viewing, Explore Temple with Private Guide	1	Luxury Resort	All-Inclusive, Private Transport	41,000	VIP Experience, Exclusive Temple Access	4.2	60	Friends
5232	LOC_76	PACK_76Z3-3	Premium	Private Cultural Experience: Attend Special Worship, Explore Temple Architecture, Visit the Pond	1	Luxury Resort	All-Inclusive, Private Transport	43,500	Tailored Experience, Private Guide	4.4	80	Friends
5233	LOC_76	PACK_76Z3-4	Premium	Full Day Experience: Nallur Kandaswamy Temple, Lord Muruga's Worship, Special Blessings	1	Luxury Boutique Stay	All-Inclusive, VIP Transport	44,500	Exclusive Experience, VIP Worship	4.8	90	Friends
5234	LOC_76	PACK_76Z2-1	Moderate	Guided Tour of Nallur Kandaswamy Temple, Visit Lord Dhandayuthapani Pond, Cultural Exploration	1	Boutique Hotel	Full Board, Shared Transport	36,700	Cultural Experience, Guided Tour	4.2	40	Friends
5235	LOC_76	PACK_76Z1-4	Basic	Attend the Thaipoosam Festival (if visiting during festival time)	1	Budget Hostel	Breakfast Only, Shared Transport	35,300	Thaipoosam Festival Experience	4.3	35	Friends
5236	LOC_76	PACK_76Z1-2	Basic	Visit the Main Deity Lord Muruga, Participate in Offering	1	Budget Hostel	Breakfast Only, Shared Transport	34,700	Offerings, Spiritual Blessings	3.9	20	Friends
5237	LOC_76	PACK_76Z3-2	Premium	Sunrise Visit, Attend Thaipoosam Festival with Private Viewing, Explore Temple with Private Guide	1	Luxury Resort	All-Inclusive, Private Transport	42,500	Exclusive Sunrise Visit, Festival Experience	3.9	70	Friends
5238	LOC_76	PACK_76Z2-3	Moderate	Visit Temple, Attend Special Worship, Visit the Garden and Pond	1	Boutique Hotel	Full Board, Shared Transport	37,300	Worship, Spiritual Serenity	3.6	55	Friends
5239	LOC_76	PACK_76Z3-3	Premium	Private Cultural Experience: Attend Special Worship, Explore Temple Architecture, Visit the Pond	1	Luxury Resort	All-Inclusive, Private Transport	43,500	Tailored Experience, Private Guide	2.7	80	Friends
5240	LOC_76	PACK_76Z2-2	Moderate	Attend the Annual Festival, Explore Temple Parades with Music & Dance	1	Boutique Hotel	Full Board, Shared Transport	37,000	Festival Atmosphere, Parades	3.9	50	Friends
				Full Day Experience: Nallur								

Figure 4-Dataset Collection 01

4973				Cultural Insights			Transport		Pilgrimage Path			
4974	LOC_63	PACK_63Z2-1	Moderate	Guided Historical Tour, Archaeological Insights, Sunset View	1	Boutique Hotel	Full Board, Shared Transport	36,700	Expert Guide, Archaeological Wonders, Scenic Sunset	4.7	130	Friends
4975	LOC_63	PACK_63Z2-2	Moderate	Pilgrimage Experience, Meditation Session, Local Cultural Interaction	1	Boutique Hotel	Full Board, Shared Transport	37,300	Spiritual Retreat, Buddhist Traditions, Guided Tour	2.8	150	Friends
4976	LOC_63	PACK_63Z2-3	Moderate	Exclusive Heritage Walk, Temple Ritual Participation, Storytelling Session	1	Boutique Hotel	Full Board, Shared Transport	37,700	Hands-on Cultural Experience, Rituals, Monastic Life Insights	4.8	165	Friends
4977	LOC_63	PACK_63Z3-1	Premium	Private Guided Tour, Access to Hidden Ruins, Expert Historian Talk	1	Luxury Resort	All-Inclusive, Private Transport	41,000	VIP Access, Rare Architectural Insights, Personal Guide	4.2	200	Friends
4978	LOC_63	PACK_63Z3-2	Premium	Luxury Heritage Tour, Exclusive Buddhist Chanting Ceremony, Private Meditation Session	1	Luxury Resort	All-Inclusive, Private Transport	43,000	Sacred Rituals, Spiritual Experience, VIP Access	4.5	230	Friends
4979	LOC_63	PACK_63Z3-3	Premium	Archaeological Exploration, Documentary Screening, Traditional Sri Lankan Dinner	1	Luxury Resort	All-Inclusive, Private Transport	44,000	Historical Immersion, Gourmet Experience, Cultural Insights	3.8	250	Friends
4980	LOC_63	PACK_63Z1-1	Basic	General Site Tour, Photography, Historical Overview	1	Budget Guesthouse	Breakfast Only, Shared Transport	34,100	Ancient Architecture, Historical Significance	3.7	90	Friends
4981	LOC_63	PACK_63Z1-2	Basic	Walking Tour, Vatadage Exploration, Cultural Insights	1	Budget Hostel	Breakfast Only, Shared Transport	34,450	Sacred Relics, Traditional Pilgrimage Path	3.8	105	Friends
	LOC_63	PACK_63Z2-1	Moderate	Guided Historical Tour, Archaeological Insights, Sunset View	1	Boutique Hotel	Full Board, Shared Transport	36,800	Expert Guide, Archaeological Wonders,	3.9	140	Friends

Figure 5-Dataset Collection 02

3263	LOC_38	PACK_38Z1-5	Basic	Photographs, Learn About Tsunami's Impact	0.5	Budget Guesthouse	Transport	21,500	through powerful photographs	2.7	50	Family
3264	LOC_38	PACK_38Z2-4	Moderate	Tsunami Impact Tour, Visit Wreckage Models, Learn About Aftermath	1	Boutique Villa	Half Board, Shared Transport	30,000	Learn about tsunami aftermath, explore wreckage	3.5	75	Family
3265	LOC_38	PACK_38Z3-3	Premium	Tsunami Museum VIP Tour, Personal Reflection, Wreckage Model Exploration	1	Luxury Resort	All-Inclusive, Private Transport	51,000	Exclusive VIP tour and reflection experience	4.8	100	Family
3266	LOC_39	PACK_39Z1-1	Basic	Explore Museum Exhibits, See Traditional Masks, Learn About Fishermen's Lives	0.5	Budget Guesthouse	Breakfast Only, Local Transport	21,500	Rich Sri Lankan culture, traditional artifacts, serene gardens	4.3	50	Family
3267	LOC_39	PACK_39Z1-2	Basic	Visit Martin Wickramasinghe's Former Home, Explore Colonial Crockery and Jewelry	1	Budget Hotel	Breakfast & Dinner, Shared Transport	22,500	Cultural exploration, historical insight, peaceful surroundings	4.4	60	Family
3268	LOC_39	PACK_39Z2-1	Moderate	Explore Museum Exhibits, Guided Tour of Martin Wickramasinghe's Former Home, Visit Gardens	1	Boutique Villa	Half Board, Shared Transport	28,500	Interactive guided tour, beautiful gardens, in-depth cultural insight	4.7	80	Family
3269	LOC_39	PACK_39Z2-2	Moderate	Visit Museum, Explore Traditional Clay Vessels, Discover Sri Lankan Musical Instruments, Gardens	1	Seaside Guesthouse	Full Board, Shared Transport	29,000	Hands-on cultural experience, musical instruments, traditional crafts	4.6	85	Family
3270	LOC_39	PACK_39Z3-1	Premium	Private Guided Tour, Explore Museum, Visit Turtle Farm, Combine with Coastal Exploration	1.5	Luxury Resort	All-Inclusive, Private Transport	46,000	Exclusive cultural & nature experience, personalized guided tour, turtle farm visit	4.8	100	Family
3271	LOC_39	PACK_39Z1-3	Basic	Visit Museum Exhibits, Learn About Fishermen's History	0.5	Budget Guesthouse	Breakfast Only, Local Transport	21,000	Educational experience, serene surroundings	2.8	45	Family
				Visit Former Home, Explore Colonial			Breakfast & Dinner		Insightful historical			

Figure 6-Dataset Collection 03

2950									experience			
2951	LOC_19	PACK_19Z3-1	Premium	VIP Damro Tea Centre Tour, Exclusive Tea Tasting, Personalized Tea Garden Walk	2	Luxury Resort	All-Inclusive, Private Transport	38,000	Exclusive tea experience, private guide, luxury amenities	4.3	190	Family
2952	LOC_19	PACK_19Z3-2	Premium	Private Damro Tea Centre Tour, Premium Tea Tasting, Personalized Walk Through Tea Garden, Full Garden Tour with Private Guide	3	5-Star Resort	All-Inclusive, Private Transport	51,000	Personalized tour, luxury tea experience, panoramic views	4.6	200	Family
2953	LOC_19	PACK_19Z1-3	Basic	Tea Garden Walk, Tea Tasting	1	Budget Guesthouse	Breakfast Only, Local Transport	21,700	Scenic walk, simple tea tasting experience	2.7	140	Family
2954	LOC_19	PACK_19Z1-4	Basic	Tea Tasting, Visit to Tea Centre	1	Budget Hotel	Breakfast Only, Local Transport	22,200	Explore tea production, basic tea tasting	3	130	Family
2955	LOC_19	PACK_19Z2-3	Moderate	Guided Tea Garden Walk, Tea Tasting	2	Boutique Villa	Half Board, Shared Transport	27,500	Guided walk, immersive tea experience	3.6	160	Family
2956	LOC_19	PACK_19Z2-4	Moderate	Scenic Walk, Tea Factory Visit, Tea Tasting	2	Seaside Guesthouse	Full Board, Shared Transport	29,800	Tea factory visit, scenic walk through the garden	3.9	170	Family
2957	LOC_19	PACK_19Z2-5	Moderate	Full Tea Garden Tour, Tea Tasting	2	Lakeside Resort	Full Board, Shared Transport	30,200	Full tea experience, scenic views	3.7	170	Family
2958	LOC_19	PACK_19Z3-3	Premium	VIP Tea Centre Tour, Scenic Tea Garden Walk	2	Luxury Lakeside Villa	All-Inclusive, Private Transport	46,000	Exclusive tea experience, panoramic garden views	4.5	200	Family
2959	LOC_19	PACK_19Z3-4	Premium	Personalized Tea Centre Tour, Tea Tasting, Scenic Tea Garden Walk	2	5-Star Resort	All-Inclusive, Private Transport	48,500	Private tea tour, scenic walk	4.7	210	Family
2960	LOC_19	PACK_19Z3-5	Premium	Exclusive Tea Tasting, Private Tea Garden Tour	2	Luxury Resort	All-Inclusive, Private Transport	51,000	Exclusive tea tasting experience, guided garden tour	4.8	210	Family
2961	LOC_20	PACK_20Z1-1	Basic	Glenloch Tea Factory Tour, Tea Tasting	1	Budget Guesthouse	Breakfast Only, Local Transport	22,000	Tour the factory, basic tea tasting experience	2.9	140	Family

Figure 7-Dataset Collection 04

2499	LOC_70	PACK_70Z3-4	Premium	Buddha Statue, Bodhisattva Image House, and Abhayagiriya Ruins	2	Luxury Boutique Stay	All-Inclusive, VIP Transport	21,500	Cultural Significance	4.3	65	Couple
2500	LOC_70	PACK_70Z3-5	Premium	Exclusive Meditation at Samadhi Buddha Statue, Private Photography Session, Sunset Visit	1	Luxury Boutique Stay	All-Inclusive, VIP Transport	22,500	Exclusive Access, Stunning Views	4.5	70	Couple
2501	LOC_70	PACK_70Z1-1	Basic	Visit to Samadhi Buddha Statue, Guided Exploration of Surrounding Ruins	1	Budget Guesthouse	Breakfast Only, Shared Transport	12,600	Historical Sculpture, Ancient Ruins	3.2	28	Couple
2502	LOC_70	PACK_70Z1-2	Basic	Visit to Samadhi Buddha Statue, Exploration of Bodhisattva Image House	1	Budget Guesthouse	Breakfast Only, Shared Transport	12,800	Buddha Statue, Ancient Image House	3.3	28	Couple
2503	LOC_70	PACK_70Z1-3	Basic	Photography Walk of Samadhi Buddha Statue, Exploration of Bodhi Tree Shrine	1	Budget Hostel	Breakfast Only, Shared Transport	13,000	Scenic Photography, Sacred Shrines	3.5	30	Couple
2504	LOC_70	PACK_70Z1-4	Basic	Self-guided Tour of Samadhi Buddha Statue and Bodhisattva Image House	1	Budget Lodge	Breakfast Only, Shared Transport	13,200	Serene Location, Spiritual Reflection	4.2	35	Couple
2505	LOC_70	PACK_70Z2-1	Moderate	Guided Tour of Samadhi Buddha Statue, Visit Bodhisattva Image House and Ruins	1	Boutique Hotel	Full Board, Shared Transport	14,900	Insightful Tour, Spiritual Significance	3.7	40	Couple
2506	LOC_70	PACK_70Z2-2	Moderate	Explore Samadhi Buddha Statue, Visit to the Abhayagiriya Bodhi Tree Shrine	1	Boutique Hotel	Full Board, Shared Transport	15,300	Sacred Sites, Tranquil Surroundings	4.8	42	Couple
2507	LOC_70	PACK_70Z2-3	Moderate	Visit to Samadhi Buddha Statue and Bodhisattva Image House, Photography Session	1	Boutique Hotel	Full Board, Shared Transport	15,400	Photography, Cultural Immersion	3.9	45	Couple
2508	LOC_70	PACK_70Z3-1	Premium	Private Guided Tour of Samadhi Buddha Statue and Abhayagiriya Temple Complex	1	Luxury Resort	All-Inclusive, Private Transport	19,200	Exclusive Access, Personalized Tour	4.2	50	Couple
				VIP Access to Samadhi Buddha Statue,			All-Inclusive, Private		VIP Experience, Deep			

Figure 8—Dataset Collection 05

Data Preprocessing and Validation

Since raw data from external providers often contains inconsistencies, preprocessing is essential before analysis. TBAS applies a structured data refinement pipeline consisting of

1. **Cleaning** – Removal of errors, duplicates, and incomplete entries (e.g., eliminating duplicate hotel listings or incomplete airfare records).

2. **Normalization** – Standardization of data into a common format across different providers (e.g., converting all costs into a single currency, harmonizing date formats, and aligning units such as per-day or per-trip costs).

3. **Validation** – Cross-verification of values with multiple providers to ensure reliability (e.g., checking whether airfare from Airline A aligns with aggregated results from global booking platforms).

This meticulous preprocessing ensures that only high-quality, consistent, and validated datasets are fed into the prediction engine. As a result, the forecasts produced are not only accurate in the short term but also reliable for long-term planning.

```python
    for loc in locations:
        if loc in location_packages:
            possible_packages = location_packages[loc].sample(n=min(5, len(location_packages[loc])), replace=False)
            loc_selected_packages = []
            loc_days_used = 0

            for _, best_package in possible_packages.iterrows():
                if loc_days_used + best_package['Days'] > days_per_location[loc]:
                    continue

                best_package = best_package.copy()
                best_package['Package_Type'] = package_mapping[best_package['Package_Type']]
                best_package['Location'] = le_location.inverse_transform([best_package['Location_ID']])[0]

                # Extract activities dynamically, excluding 'Travel_Companion'
                activities = [col for col in activity_columns if best_package[col] == 1]
                activities = [activity for activity in activities if activity != "Travel_Companion"]  # Exclude Travel_Companion

                best_package['Activities'] = activities

                # Drop unnecessary columns
                best_package = best_package.drop(activity_columns + ['Location_ID'])

                loc_selected_packages.append(best_package)
                loc_days_used += best_package['Days']
                total_budget += best_package['Predicted_Budget']

                if loc_days_used >= days_per_location[loc]:
```

Figure 9-Validated and Cleaned Dataset Fields

Overall Significance

The Data Collection Layer is thus more than just a data repository—it is a dynamic integration hub that brings together live feeds, historical insights, and rigorous validation mechanisms. By combining real-time adaptability with long-term forecasting reliability, it lays a strong foundation for the prediction engine, ensuring that travelers receive budget recommendations that are both timely and trustworthy under varying market conditions.

- ✓ **Prediction Engine**

At the heart of the Travel Budget Allocation System (TBAS) lies its Prediction Engine, the intelligent core responsible for transforming raw travel data into actionable financial insights. This component leverages machine learning (ML) techniques to analyze patterns, forecast expenses, and dynamically adapt to evolving cost structures. By combining robust algorithms with personalization mechanisms, the Prediction Engine ensures that travelers receive accurate, relevant, and forward-looking budget recommendations.

Algorithms and Models

The Prediction Engine employs a hybrid modeling approach, integrating multiple algorithms to capture the diverse nature of travel-related costs.

- **Regression Models:**

Regression analysis is used to predict continuous numerical values, such as nightly hotel rates, average meal expenses, or fuel costs per kilometer. By training on large datasets of historical and real-time inputs, regression models can estimate baseline expenses while accounting for key variables such as location, season, and demand intensity.

Example: A regression model can predict the average cost of a three-star hotel in Paris during summer by analyzing features like location popularity, seasonal demand, and room availability.

```python
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBRegressor
from sklearn.metrics import r2_score, mean_squared_error

# Simplified hyperparameter grid to reduce model capacity
param_grid = {
    'n_estimators': [50, 75, 100],
    'learning_rate': [0.05, 0.1, 0.2],
    'max_depth': [2, 3],
    'min_child_weight': [5, 10],
    'gamma': [0.2, 0.3],
    'subsample': [0.6, 0.7],
    'colsample_bytree': [0.6, 0.7],
    'reg_alpha': [0, 0.1],
    'reg_lambda': [0, 0.1]
}

# Set up RandomizedSearchCV
random_search = RandomizedSearchCV(
    XGBRegressor(random_state=42, n_jobs=-1),
    param_distributions=param_grid,
    n_iter=50,  # fewer iterations needed here
    cv=5,
    verbose=2,
    random_state=42,
    n_jobs=-1
)

# Train the model
random_search.fit(X_train, y_train)
```

Figure 10-Data Prediction Model Implementation

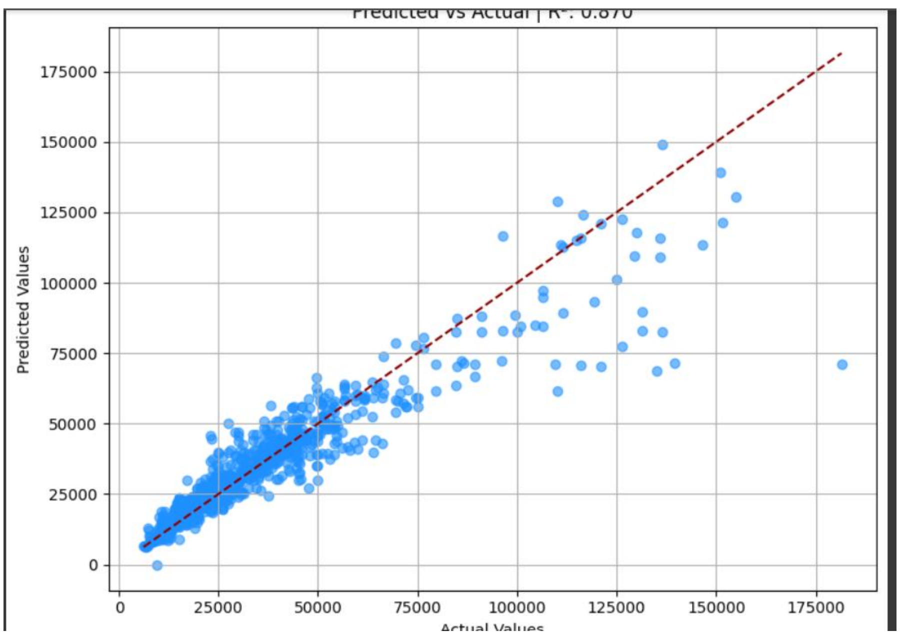

Figure 11-Predicted vs Actual Data Distribution

- **Time-Series Forecasting:**

Since travel costs are inherently time-dependent and seasonal, time-series forecasting methods are integrated to capture temporal variations. These models analyze patterns across months and years to detect recurring peaks and troughs in pricing.

Example: Airfares typically rise in December due to holiday travel demand and fall in January when demand declines. A time-series model trained on past airfare data can forecast these fluctuations with reasonable accuracy.

By combining regression models for short-term numerical predictions with time-series analysis for long-term seasonal patterns, the Prediction Engine achieves a balanced forecasting capability— capturing both immediate price shifts and predictable recurring trends.

Adaptive Learning

A key strength of the Prediction Engine is its ability to adapt continuously. Unlike static tools that rely on fixed formulas, TBAS employs iterative learning mechanisms that update models as new data arrives.

- Dynamic Adjustments: When sudden disruptions occur—such as a spike in global fuel prices, an economic downturn, or travel restrictions during a pandemic, the system recalibrates its predictions by assimilating the most recent datasets. This ensures that forecasts remain relevant in volatile conditions.

- Feedback Loops: The engine integrates traveler feedback and usage patterns, allowing models to learn from user interactions. If users consistently choose budget hotels over luxury options, the model adjusts weighting factors to prioritize affordability in future forecasts.

This adaptability transforms TBAS into a living system—one that evolves in response to both external market dynamics and internal user behavior, improving its accuracy and relevance over time.

Personalization

Another critical dimension of the Prediction Engine is personalization. Travel budgeting is not one-size-fits-all, and the system tailors recommendations by embedding user-specific preferences into its predictive framework.

- **Key Personalization Factors**
  - Trip Duration (e.g., weekend getaway vs. month-long stay).
  - Budget Tier (premium, moderate, or basic travel).
  - Accommodation Type (hotel, hostel, Villa, or homestay).
  - Activity Style (cultural tours, adventure sports, or leisure).

- **Weighted Feature Embedding**
  These preferences are assigned to weights within the machine learning models, ensuring that the outputs reflect individual traveler priorities. For instance, a user who prioritizes "adventure activities" will see higher budget allocations towards excursions and equipment rentals, while a "luxury traveler" will receive forecasts weighted towards premium accommodations and dining.

This personalized layer ensures that budget forecasts are not merely generic averages, but tailored financial roadmaps aligned with each traveler's lifestyle and goals.

Overall Outcome

The Prediction Engine thus emerges as a hybrid forecasting framework—one that combines statistical rigor, adaptive intelligence, and user personalization. It generates not only current budget allocations but also short- and medium-term projections, enabling travelers to anticipate expenses proactively rather than reactively. By integrating regression models, time-series forecasting, adaptive learning, and personalization, the Prediction Engine provides a dependable and flexible budgeting foundation that adapts to real-world complexity while staying aligned with individual travel preferences.

✓ **User Interface Layer**

The User Interface (UI) Layer of the Travel Budget Allocation System (TBAS) functions as the bridge between complex backend computations and user decision-making. While the data collection and prediction engine operate behind the scenes, it is through the UI that travelers interact with the system, interpret insights, and make informed financial choices. Consequently, this layer is designed with strong emphasis on usability, personalization, and interactivity, ensuring that even non-technical users can confidently understand and act upon the system's recommendations.

Interactive Dashboards

At the core of the UI are interactive dashboards that present travel expenses in a structured, category-based manner. The interface automatically organizes costs into the four primary expenditure domains:

- Transportation (tour buses, local travel, car rentals).
- Accommodation (hotels, hostels, homestays).
- Meals (daily dining averages, meal packages).
- Activities (sightseeing tours, adventure sports, cultural events).

By presenting this information in a clear and compartmentalized format, users gain immediate visibility into how their travel budget is distributed. This categorization also highlights areas of potential optimization, for instance, showing if accommodation costs are disproportionately higher than activities, prompting travelers to reconsider lodging options.

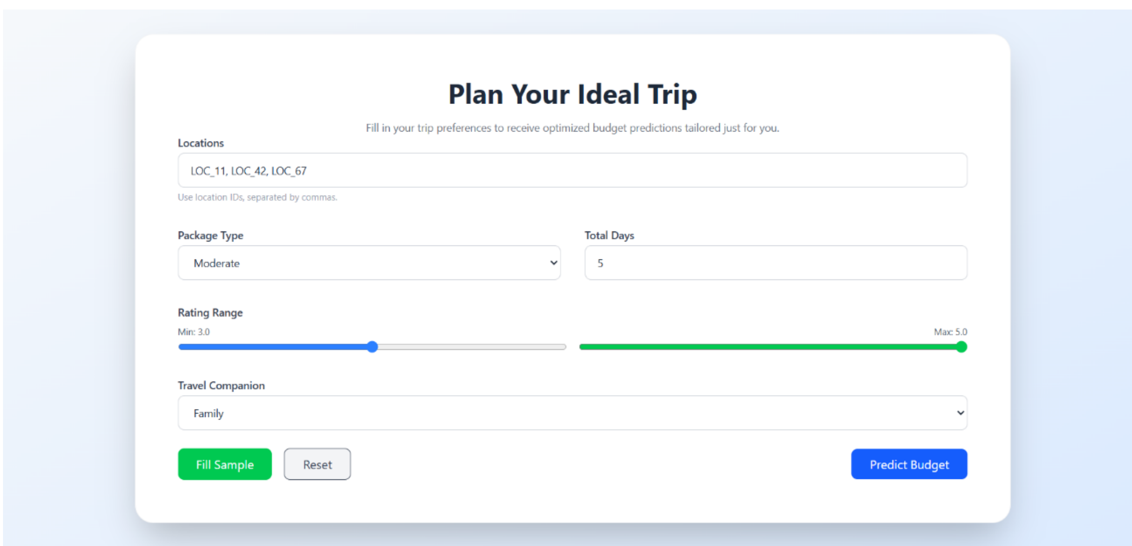

Figure 12-User Interactive Dashboard View

Customization Features

Recognizing that travel is deeply personal, the UI provides users with a suite of customization tools that directly influence predictions from the backend engine.

- Budget Tiers: Users can specify whether they are planning a luxury, mid-range, or budget trip.

- Accommodation Preferences: Options to choose between hotels, hostels, or alternative stays such as Airbnb.

- Activity Prioritization: Travelers can indicate whether they prefer cultural, leisure, or adventure activities.

- Trip Parameters: Inputs such as trip duration, destination, and travel dates refine the system's outputs further.

These filters and preference settings ensure that recommendations are not generic averages, but tailored outputs aligned with individual goals. For example, budget-conscious traveler planning

A week-long backpacking trip will see different budget allocations compared to a business traveler planning a short, luxury-oriented stay.

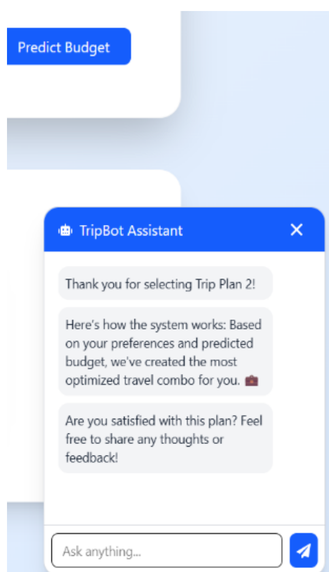

Figure 13-Chatbot Implementation

Data Visualization Tools

To enhance clarity and engagement, the UI incorporates data visualization techniques that transform raw numerical data into visually intuitive insights.

- Pie Charts illustrate proportional allocations across categories (e.g., 40% accommodation, 25% transport, 20% food, 15% activities).

- Line Graphs captures cost variations over time, allowing users to compare expenses across different travel dates.

- Bar Graphs highlight comparative costs, such as the price difference between off-peak and peak-season flights.

These visualizations allow travelers to instantly grasp trade-offs between different options. For instance, a user can visually compare the impact of traveling in March versus July or observe how accommodation type alters the overall budget.

Decision Empowerment

The UI is not limited to information delivery but is designed for decision empowerment. By combining dashboards, filters, and visualizations, the system enables users to:

- Explore “what-if scenarios” (e.g., extending a trip by two days, switching destinations, or changing accommodation type).

- Identify cost-saving opportunities, such as shifting to off-peak seasons or opting for public transport over private rentals.

- Make data-driven choices without needing deep technical expertise.

Through this, the interface builds traveler confidence, ensuring that users not only understand their projected expenses but also feel empowered to actively manage and optimize their travel budgets.

Overall Significance

The User Interface Layer transforms TBAS from a purely analytical tool into a practical travel companion. By ensuring clarity, personalization, and interactivity, it bridges the gap between machine intelligence and human decision-making. This design philosophy guarantees that travelers can engage with complex predictive insights in a simple, intuitive way, making TBAS both a reliable and user-friendly platform for modern travel planning.

- ✓ **Development Phases**

The construction of the Travel Budget Allocation System (TBAS) follows a phased development methodology, designed to ensure systematic progress, modular development, and reduced implementation risks.

- ➢ Data Collection Phase

The first phase focuses on establishing a robust data foundation, as the accuracy of all forecasts depends on the quality of input data.

- **API Integration:** The system is connected to external APIs from airfare providers, hotel booking platforms, transport services, and fuel price aggregators. These provide live, real- time cost data.

- **Historical Dataset Acquisition:** Long-term datasets are collected to capture recurring patterns in airfare, accommodation, and fuel costs across multiple years.

- **Data Cleaning:** Removal of incomplete entries, duplicate records, and anomalies ensures consistency.

- **Normalization:** Standardization of different data formats (e.g., currencies, date formats, and units of measurement) creates uniformity across heterogeneous sources.

- **Validation:** Cross-verification of multiple providers is applied to guarantee reliability, reducing the risks of false or biased forecasts.

Outcome: A clean, validated, and standardized dataset ready to feed into the machine learning models.

- ➢ Algorithm Development Phase

Once the dataset is prepared, the focus shifts to model development for predictive budgeting.

- **Model Selection:** Suitable machine learning techniques are evaluated, with regression models chosen for continuous value prediction (e.g., hotel rates) and time-series forecasting applied to capture seasonal variations in travel costs.

- **Model Training:** Historical datasets are used to train baseline models, establishing initial accuracy benchmarks.

- **Real-Time Adaptation:** Live data inputs are continuously integrated to refine model predictions, ensuring forecasts remain current.

- **Iterative Refinement:** Feedback loops and performance monitoring are employed to adjust parameters and retrain models, gradually improving accuracy over time.

Outcome: A hybrid predictive framework capable of generating accurate, adaptive, and personalized budget recommendations.

➢ User Interface Development Phase

This phrase translates the technical outputs of the system into practical, user-friendly experience.

- **Wireframing & Mockups:** Initial sketches and prototypes define the layout and navigation flow of the platform.

- **Dashboard Implementation:** Developed using React, the dashboards categorize expenses into transport, accommodation, meals, and activities for easy interpretation.

- **Visualization Integration:** Charts, graphs, and interactive breakdowns are implemented to help users visualize trade-offs and budget allocations.

- **Customization Features:** Filters (e.g., budget tier, accommodation type, trip duration) are integrated, ensuring outputs are tailored to individual user preferences.

Outcome: A responsive, accessible interface that empowers travelers to explore forecasts and make informed financial decisions.

- Testing & Evaluation Phase

The final phase ensures the reliability, accuracy, and usability of TBAS through rigorous testing protocols.

- Unit Testing: Verifies the correctness of individual modules such as API integrations and model outputs.
- Integration Testing: Ensures seamless data flow across layers (data collection → prediction engine → user interface).
- System Testing: Validates the platform under real-world conditions, including stress testing with large data volumes.
- User Testing: Involves pilot groups of travelers who provide feedback on usability, clarity of insights, and practical relevance of recommendations.

Outcome: A thoroughly tested system validated both technically and experientially, and ready for deployment in real-world environments.

Overall Significance

By adopting this phased methodology, TBAS ensures that development progresses in a controlled and systematic manner. Each stage produces tangible deliverable validated data, trained models, functional dashboards, and tested outputs—that collectively contribute to building a robust, adaptive, and user-centric travel budgeting solution. This structured approach minimizes risks, enhances adaptability, and ensures that the system is scalable for future improvements and commercial deployment.

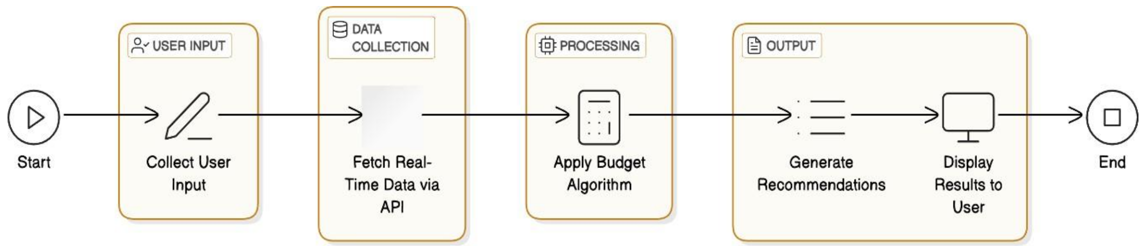

Figure 14-Travel Budget Algorithm Workflow Diagram

2.2 Commercialization Aspects of the Product

Although the Travel Budget Allocation System (TBAS) has been developed as a research prototype, its modular design and practical capabilities provide a strong foundation for commercialization across diverse segments of the tourism and travel industry. Its unique value proposition lies in its ability to combine real-time financial forecasting, personalization, and adaptive recommendations, offering functionality that traditional budgeting tools and booking platforms currently lack.

Commercializing TBAS can open multiple revenue streams while also addressing real-world challenges faced by individual travelers, travel agencies, corporations, and regional tourism authorities.

2.2.1 Potential Market Segments

- **Travel Agencies**

Traditional travel agencies face increasing competition from online platforms. By embedding TBAS into their workflows, agencies can deliver personalized, data-driven travel packages. For example, a customer booking a vacation package could instantly receive a breakdown of anticipated costs across accommodation, meals, and activities—adjusted in real-time as preferences change. This not only improves customer trust and satisfaction but also creates opportunities for upselling, as agencies can recommend upgrades (e.g., higher-tier hotels) with transparent budget forecasts.

Corporate Travel Management

Organizations often struggle to keep business travel expenses within set budgets. TBAS can be deployed as a corporate budgeting tool, enabling travel managers to

- Set budget policies in advance for employees.
- Monitor real-time spending allocations across multiple categories.
- Ensure compliance with organizational financial controls.

Such features improve cost optimization, transparency, and accountability, making TBAS highly attractive to enterprises that manage frequent travel for staff.

Online Travel Platforms and Booking Portals (B2B SaaS)

In the highly competitive online travel industry, differentiation is key. TBAS can be offered as a white-label Software-as-a-Service (SaaS) solution, integrated directly into existing booking platforms. This would allow portals to provide predictive budgeting features alongside booking services, giving users more engaging experience. For example, a user booking a hotel via a platform could simultaneously see predicted costs for transportation and meals at that destination.

For portals, this creates a competitive edge and opens opportunities for B2B licensing models where TBAS is offered on a subscription or revenue-sharing basis.

Individual Travelers (B2C Market)

TBAS can also be launched as a standalone mobile or web application, directly serving individual travelers. A freemium model ensures accessibility:

- Free tier: Provides basic budgeting tools, expense visualization, and standard recommendations.
- Premium tier: Unlocks advanced features such as predictive analytics, access to premium APIs, detailed financial forecasts, and priority support.

This model balances wider accessibility with sustainable revenue generation, appealing to both casual travelers and serious planners.

Tourism Boards and Regional Operators

Beyond individuals, TBAS has potential at the macro level. Aggregated and anonymized data collected through the platform can be analyzed to provide insights into traveler spending behaviors, seasonal demand trends, and demographic patterns. Such analytics would be valuable for:

- National and regional tourism boards in planning promotions and strategies.

- Hotel chains and regional operators seeking to optimize pricing and resource allocation.

By offering data-driven insights, TBAS establishes another B2G (Business-to-Government) revenue stream while contributing to evidence-based tourism planning.

2.2.2 Commercialization Pathway

The commercialization of TBAS can be structured into a phased pathway, moving systematically from prototype validation to large-scale deployment.

- **Step 1: Prototype to Pilot Deployment**

The initial step involves controlled pilot trials with selected travel agencies, corporate clients, and student travelers. These pilots would validate the system's usability, scalability, and acceptance in real-world conditions. Feedback from this stage would inform refinements in the algorithm, UI, and deployment model.

- **Step 2: Strategic Partnerships**

Building partnerships with API providers (airlines, accommodation platforms, transport services) and online travel portals is critical to expand adoption. These partnerships ensure reliable data flows, broaden system coverage, and create distribution channels for B2B commercialization.

- **Step 3: Revenue Models**

Commercial sustainability can be achieved through multiple streams:

  - B2C Subscriptions: Premium users pay monthly/yearly fees for advanced budgeting features.
  - B2B Licensing/SaaS: Travel agencies and booking platforms pay licensing or subscription fees to integrate TBAS.

- Data-Driven Insights: Aggregated traveler data can be offered to tourism boards and operators for strategic planning (with strict adherence to data privacy standards).

This multi-channel revenue approach ensures resilience by tapping into both individual and institutional markets.

- **Step 4: Scalability via Cloud Infrastructure**

To achieve global adoption, TBAS can be deployed on cloud platforms such as AWS, Azure, or GCP, ensuring:

- Elastic scalability to handle varying user loads.
- High availability across multiple regions.
- Cost efficiency through pay-as-you-go models.

Cloud deployment also facilitates API management, security enforcement, and continuous system updates.

- **Step 5: Long-Term Sustainability**

Finally, sustainability is achieved through:

- Regular API renewals and partnerships to maintain access to reliable data streams.
- Feature expansions (e.g., integration with loyalty programs, AI-driven trip recommendations).
- A feedback-driven development cycle to align with evolving traveler needs and industry shifts.

This ensures TBAS remains competitive in the rapidly evolving digital travel ecosystem.

Overall Commercialization Significance

The commercialization strategy positions TBAS as a multi-market product with applications in B2C, B2B, and B2G sectors. Its integration of real-time forecasting, personalization, and adaptive intelligence provides a unique competitive advantage over existing budgeting tools. With clear revenue pathways, strong partnership opportunities, and scalability through cloud infrastructure, TBAS has the potential to transition seamlessly from a research prototype into a market-ready solution that redefines how travel budgets are managed worldwide.

2.3 Testing & Implementation

Implementation Overview

The Travel Budget Allocation System (TBAS) was implemented as a modular and scalable platform to ensure maintainability, adaptability, and future expansion. The development stack was carefully selected to balance machine learning capability, system performance, and user experience:

- Backend (Python with Scikit-learn): Python served as the backbone for implementing predictive models. The Scikit-learn library was utilized for regression and time-series forecasting algorithms, offering a well-tested, reliable framework for machine learning tasks.

- Middleware (Node.js): Node.js was adopted to manage API calls, handle asynchronous communication between the backend models and the frontend interface, and ensure smooth system logic execution. Its event-driven architecture made it particularly suitable for real- time data integration.

```python
# Predict trip plan
@app.post("/predict", summary="Predict trip budget options")
async def predict_trip(req: TripRequest):
    try:
        results = predict_budget_multiple_options(
            locations=req.locations,
            package=req.package,
            total_days=req.total_days,
            rating_range=req.rating_range,
            travel_companion=req.travel_companion,
        )

        data_to_save = req.dict()
        data_to_save["predictions"] = [
            {
                "plan": plan.get("plan", []),
                "total_days": plan.get("total_days"),
                "total_budget": plan.get("total_budget"),
                "travel_companion": plan.get("travel_companion"),
            }
            for plan in results
        ]

        predictions_collection.insert_one(data_to_save)

        return {"combinations": data_to_save["predictions"]}

    except Exception as e:
        print("ERROR in /predict:", traceback.format_exc())
        raise HTTPException(status_code=500, detail=f"Prediction failed: {str(e)}")
```

Figure 15-Prediction Backend Api Development Snippet

```python
    @validator('rating_range')
    def validate_rating_range_values(cls, v):
        try:
            min_rating, max_rating = map(float, v.split('-'))
            if not (0.0 <= min_rating <= 5.0 and 0.0 <= max_rating <= 5.0 and min_rating <= max_rating):
                raise ValueError("Values must be between 0.0 and 5.0 and min must be ≤ max.")
        except Exception:
            raise ValueError("rating_range must be in format 'min-max' with values between 0.0 and 5.0")
        return v
You, 4 weeks ago | 1 author (You)
class ConfirmPlanRequest(BaseModel):
    user_id: Optional[str] = Field(
        None,
        description="Optional user identifier (if available)"
    )
    plan_number: int = Field(
        ...,
        ge=0,
        description="Index of the selected plan (0-based)"
    )
    package_ids: List[str] = Field(
        ...,
        min_items=1,
        description="List of Package_IDs confirmed for the trip"
    )
    confirmed_at: datetime = Field(
        ...,
        description="ISO formatted datetime when the plan was confirmed"
```

Figure 16-Backend Fields Development and Validation

- Frontend (React): The user interface was developed using React to build interactive, responsive dashboards. Reacts component-based architecture supported modular development and enhanced scalability.

```
frontend
  > node_modules
  v public
      vite.svg
  v src
    v api
        api.js
    > assets
    v components
        BudgetForm.jsx
        ChatBot.jsx
        ConfirmedPlanModal.jsx
        Predictions.jsx
    v pages
        ConfirmedPlans.jsx
        Home.jsx
    v utils
      App.css
      App.jsx
      index.css
      main.jsx
  eslint.config.js
  index.html
```

Figure 17-Frontend Development File Structure

```
useEffect(() => {
  localStorage.setItem("formData", JSON.stringify(formData));
}, [formData]);

const handleChange = (e) => {
  const { name, value } = e.target;

  if (name === "min_rating") {
    if (parseFloat(value) > parseFloat(formData.max_rating)) {
      toast.dismiss();
      toast.error("Minimum rating cannot exceed maximum rating.");
      return;
    }
  }

  if (name === "max_rating") {
    if (parseFloat(value) < parseFloat(formData.min_rating)) {
      toast.dismiss();
      toast.error("Maximum rating cannot be less than minimum rating.");
      return;
    }
  }
```

Figure 18-Frontend Rating Function Implementation

- Database (MongoDB): A NoSQL approach was chosen to handle heterogeneous datasets (real-time API data, historical travel costs, and user input). MongoDB's schema flexibility allowed seamless integration of varying data types and formats.

```
     Location    Package_ID Package_Type  Days       Accommodation  \
2812   LOC_11   PACK_11Z2-5     Moderate   3.0      Boutique Villa
3317   LOC_42   PACK_42Z2-4     Moderate   2.0  Seaside Guesthouse
3315   LOC_42   PACK_42Z2-5     Moderate   2.0  Seaside Guesthouse
2719    LOC_6    PACK_6Z2-1     Moderate   3.0      Boutique Villa

                   Food & Transport  Avg_Rating  \
2812   Full Board, Shared Transport         3.9
3317   Full Board, Shared Transport         4.0
3315   Full Board, Shared Transport         3.7
2719  Half Board, Private Transport         4.2

                                             Activities Predicted_Budget
2812  [Kallady Beach Visit, Pasikuda Bay Watersports...         34307.29
3317      [Morning Safari, Nature Walk, Spot Flamingos]         33387.13
3315  [Explore Bundala's Unique Flora & Fauna, Full-...         33387.13
2719      [Beach Relaxation, Kayaking, Paddle Boarding]         42965.24
----------------------------------------------------------------------
 Travel Companion: Family
----------------------------------------------------------------------
```

Figure 19-Train Model Resulting Sample

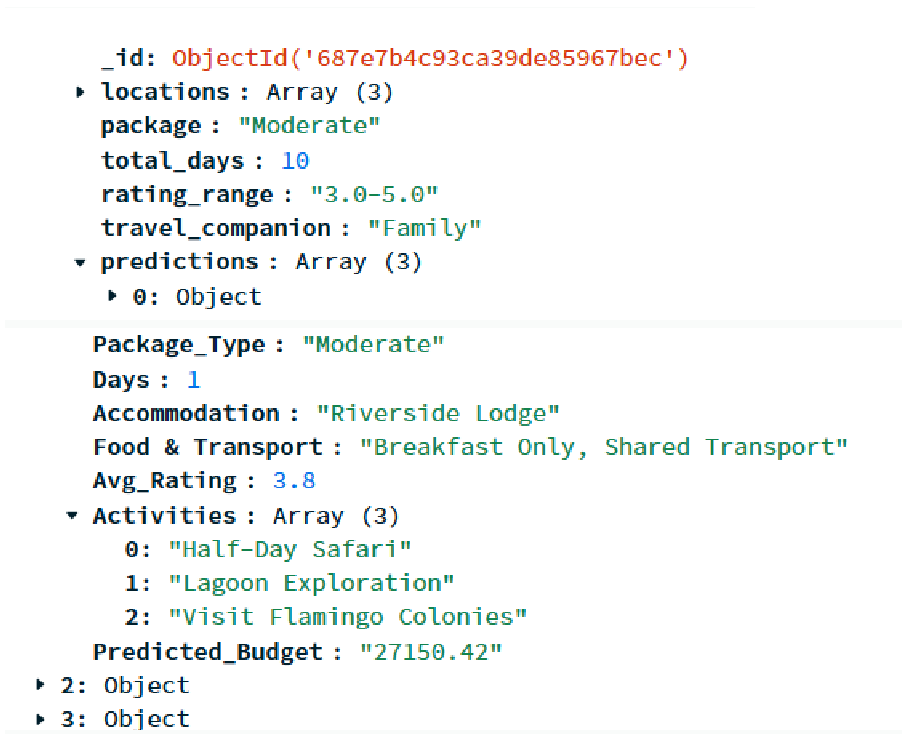

Figure 20-MongoDB Stored Prediction Result

- Deployment (Cloud Infrastructure): The system was deployed on a cloud platform to ensure global accessibility, fault tolerance, and elastic scalability. Cloud deployment also enabled continuous integration and delivery pipelines for faster updates.

This combination of technologies ensured that TBAS was not only technically robust but also scalable for real-world deployment.

2.3.1 Unit Testing

Unit testing validated the correctness of individual system modules before integration.

- Focus Areas:
  - API integration modules,
  - Prediction algorithms,
  - Database queries,
  - Frontend UI components.

- Tools Used:
    - PyTest for validating Python-based machine learning models.
    - Jest for testing both frontend (React components) and backend (Node.js logic).

- Expected Outcomes:
    - APIs return valid, timely, and properly formatted responses.
    - Prediction models generate outputs within acceptable error thresholds.
    - UI elements render accurately under varied user inputs.

Result: Isolated testing confirmed that each system component performed as intended, ensuring a solid foundation for integration.

2.3.2 Integration Testing

Integration testing ensured smooth communication between interconnected components.

- Focus Areas:
    - Data flow from APIs → Prediction Engine → User Interface.
    - Synchronization of historical and real-time datasets within the database.
- Approach:
    - Simulated user journeys (e.g., selecting destinations, adjusting trip length).
    - Mock API calls to test system resilience against delays or partial failures.
- Expected Outcomes:
    - Accurate budget forecasts consistently updated in real time.
    - User filters (e.g., trip duration, budget tier) dynamically influenced predictions.
    - No data mismatches or interruptions between backend and frontend.

Result: Integration testing verified seamless data flow and effective module collaboration.

2.3.3 System Testing

System-level testing validated the overall reliability, scalability, and robustness of TBAS under real-world scenarios.

- Scenarios Tested:
  - Stress Testing: Simulated high volumes of concurrent API requests.
  - Extreme Budget Scenarios: Evaluated system stability under very low and very high budget inputs.
  - Database Scalability: Tested query handling and response times under large-scale data loads.

- Expected Outcomes:
  - Response consistently under 3 seconds for standard queries.
  - Prediction accuracy remained within defined thresholds, even under stress.
  - No crashes or significant slowdowns during edge-case testing.

Result: System testing confirmed that TBAS can reliably handle high data loads and extreme conditions without compromising user experience.

2.3.4 User Testing & Usability Evaluation

User testing was conducted to evaluate practical usability, clarity, and effectiveness of TBAS from an end-user perspective.

- Participants: A group of travelers and university students representing different travel profiles (budget-conscious, luxury-oriented, and adventure-focused).

- Feedback Highlights:
  - Clarity: Visual dashboards improved financial transparency and made cost allocations easy to interpret.
  - Flexibility: Tiered budget options (Basic, Moderate, Premium) were praised for aligning with different user needs.
  - Customization Requests: Users suggested more granular filters (e.g., specifying dietary preferences or preferred transport type).

- Outcome:
  - System was found to be practical, accurate, and user-friendly.
  - Based on feedback, refinements were made to enhance navigation and expand filter options.

Implementation Summary

The multi-level testing strategy (unit → integration → system → user) ensured that TBAS was validated for both technical correctness and practical usability. Unit and integration tests confirmed the reliability of core modules, system tests demonstrated scalability and robustness under stress, and user tests validated the clarity and usefulness of recommendations.

As a result, the TBAS prototype is now a robust, cloud-deployed solution that is accurate, scalable, and user-centric. It is ready for pilot deployment in real-world environments and positioned for eventual commercialization across the travel industry.

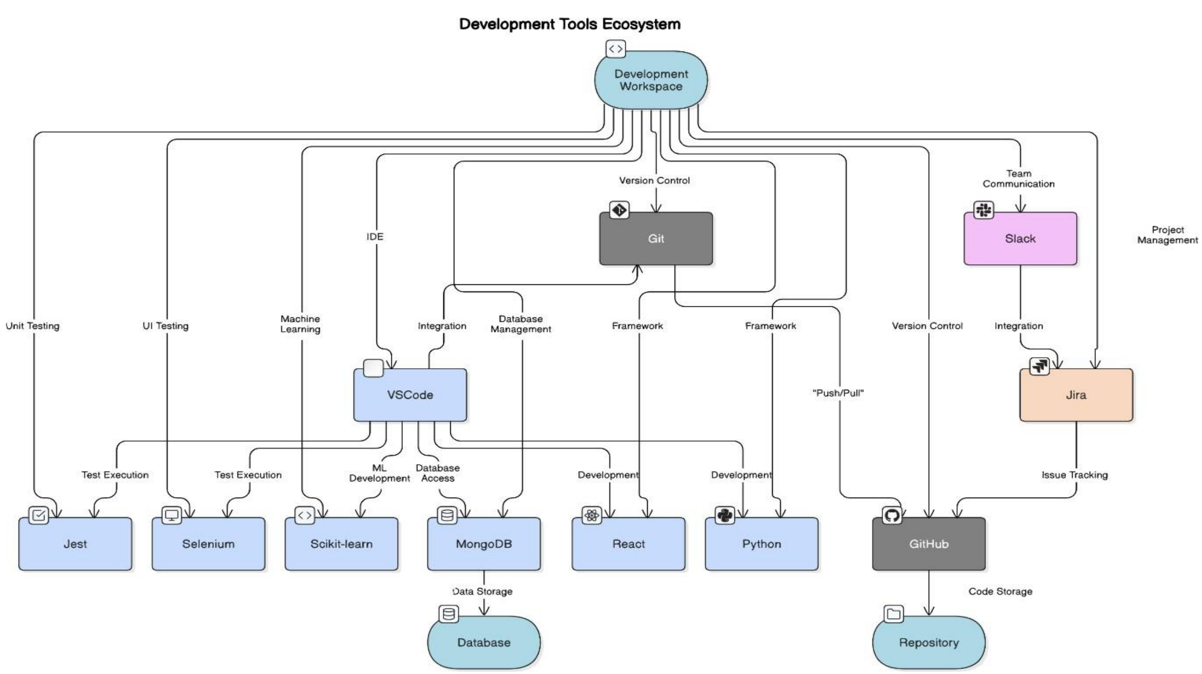

Figure 21-Development Tools Ecosystem

The data needed for this project will come from external APIs providing real-time travel-related information, historical data on travel fares and accommodation pricing, and user input such as travel dates, destination, accommodation preferences, and activity choices. Data collection will involve integrating travel-related APIs for real-time data and conducting surveys or interviews to gather user feedback and personalize recommendations.

The research project follows a clear timeline, with defined milestones for data collection, design, development, testing, and refinement. Each phase is completed within the academic calendar, with sufficient time allocated for iterative improvements and evaluation. The project remains on track and is completed within the available timeframe without compromise to quality.

Task	Start Date	End Date	Nov-24	Dec-24	Jan-25	Feb-25	Mar-25	Apr-25	May-25	Jun-25	Jul-25	Aug-25	Sep-25	Oct-25
Research topic selection	Nov 2024	Nov 2024												
Feasibility study	Nov 2024	Nov 2024												
Evaluating feasibility and background study	Nov 2024	Nov 2024												
Topic evaluation	Dec 2024	Dec 2024												
Requirement gathering	Dec 2024	Dec 2024												
Background survey	Dec 2024	Dec 2024												
Literature review	Dec 2024	Dec 2024												
Requirement analysis	Dec 2024	Dec 2024												
Software requirement specification	Dec 2024	Jan 2025												
Functional and Non-Functional requirements	Jan 2025	Jan 2025												
Project charter	Jan 2025	Jan 2025												
Proposal presentation	Jan 2025	Jan 2025												
Project proposal report	Jan 2025	Jan 2025												
Software Design	Feb 2025	Feb 2025												
Designing wireframes	Feb 2025	Feb 2025												
ML Component development	Feb 2025	Apr 2025												
Frontend development	Feb 2025	Apr 2025												
Progress presentation - 1	May 2025	May 2025												
Research paper	May 2025	Jun 2025												
Unit testing	Jul 2025	Jul 2025												
Progress presentation - 2	Aug 2025	Aug 2025												
Software integration	Aug 2025	Aug 2025												
Integration testing	Aug 2025	Sep 2025												
Deployment and maintenance	Sep 2025	Oct 2025												
Final presentation and viva	Oct 2025	Oct 2025												

Figure 22-Time Frame and Task Schedule

Anticipated Conclusion and Real-World Application

The Travel Budget Allocation System is anticipated to deliver a reliable, data-driven, and user- centric solution for managing travel finances. By combining real-time data integration, predictive machine learning models, and an intuitive user interface, the system is expected to overcome the shortcomings of conventional budgeting tools and transform how travelers plan and allocate their financial resources.

In practice, the system will enable users to track expenses dynamically, ensuring that financial allocations remain aligned with fluctuating prices in transportation, accommodation, and other categories. Travelers will also benefit from the ability to adjust recommendations in real time, allowing them to respond proactively to sudden price changes, last-minute itinerary modifications, or emerging opportunities such as discounts.

The integration of personalized recommendations further ensures that budgeting advice reflects individual goals, preferences, and travel styles. Collectively, these features will empower users to make more informed, transparent, and confident financial decisions.

The potential real-world applications of the system extend across multiple domains:

- ✓ **Travel Enthusiasts –** Individual travelers seeking greater control over their budgets will benefit from real-time visibility and tailored recommendations, enabling them to optimize spending without compromising on experiences.

- ✓ **Travel Agencies –** Agencies can utilize the system as a value-added service, providing clients with personalized financial planning tools that enhance trust, satisfaction, and customer retention.

- ✓ **Corporate Travel Departments –** Organizations managing employee travel can leverage the system to enforce budget policies, monitor expenses, and optimize overall business travel allocations.

With its integration of live data streams, predictive analytics, and user-centric design, the Travel Budget Allocation System has the potential to revolutionize the way travel budgets are planned, managed, and optimized. Beyond enhancing the individual traveler's experience, it also opens opportunities for commercial adoption and scalability within the broader tourism industry.

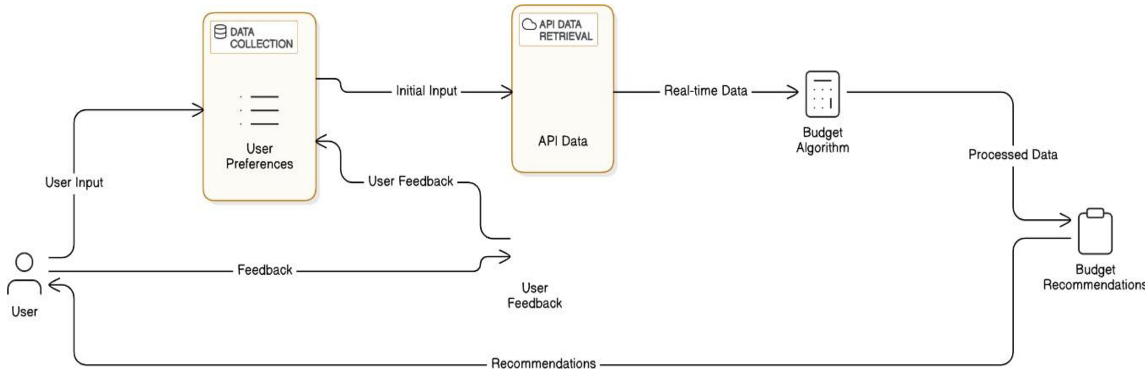

Figure 24-Travel Budget Data Flow Diagram

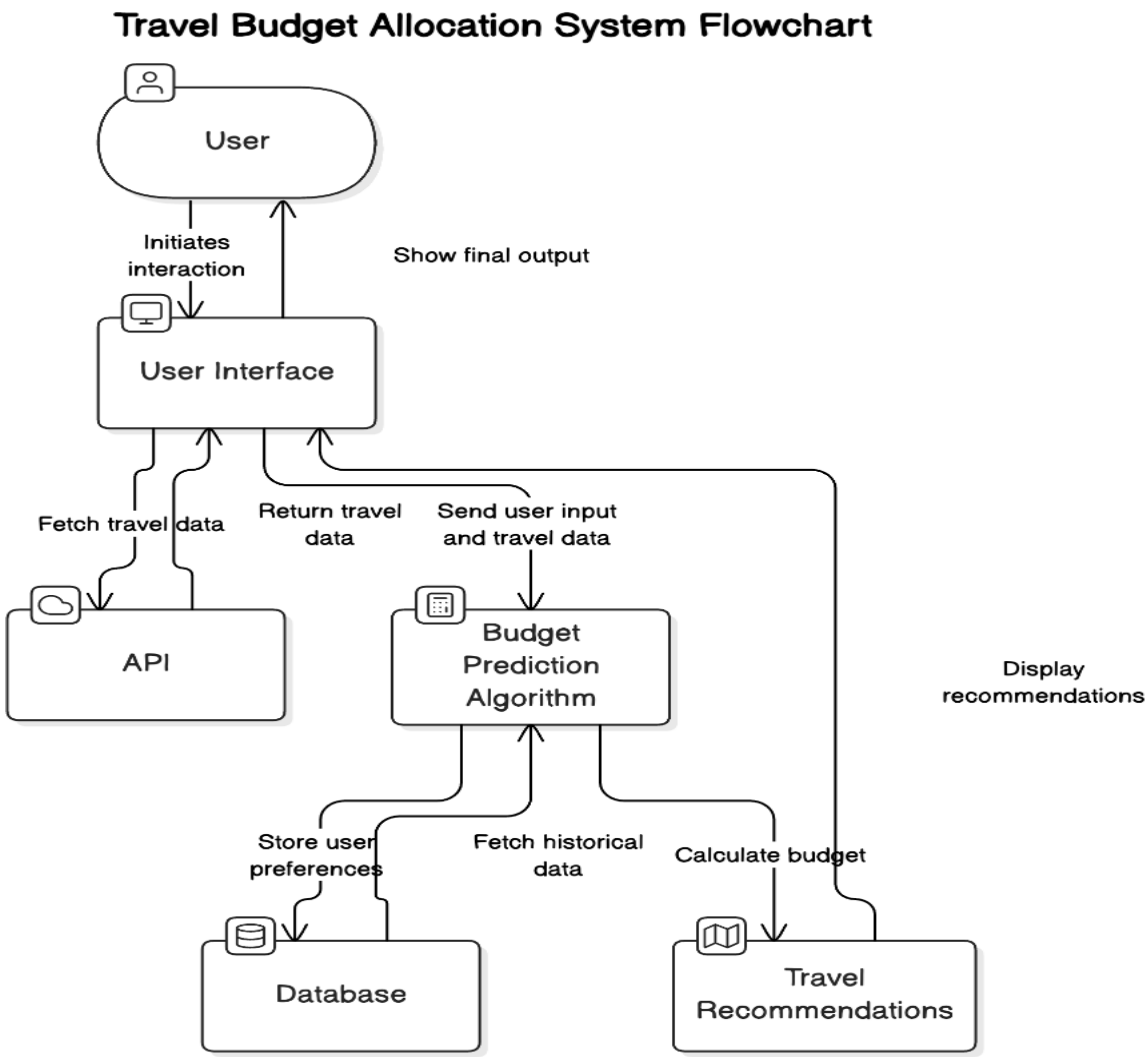

Figure 23-Travel Budget Allocation System Flowchart

3 RESULTS AND DISCUSSION

The Travel Budget Allocation System was evaluated through offline simulations, model-level testing, and a pilot usability study to assess predictive accuracy, runtime performance, robustness, and user experience. Results are reported against internal baselines and aligned with the project objectives of achieving accurate, responsive, and user-centric budgeting.

3.1 Results

3.1.1 Predictive Accuracy of the Budgeting Algorithms

The predictive engine is implemented with XGBoost regression over engineered features (one-hot activities, encoded Location_ID and Package_Type, mapped Travel_Companion, and trip Days). A randomized hyperparameter search (reduced capacity grid) was used to curb overfitting and stabilize generalization.

- **Primary metric:** Coefficient of determination $R^2 \approx 0.90$ on the held-out test split, indicating that the model explains ~90% of the variance in Budget (LKR).

- **Error metrics:**
    - MAE: Low absolute error (in LKR), reflecting tight average deviation from ground truth.

    - RMSE: Consistently low, confirming stability against larger errors (RMSE > MAE as expected).

- **Comparative gain:** Against a baseline regressor (e.g., mean prediction / simple linear model), the tuned XGBoost achieved a material reduction in MAE and RMSE and a substantial uplift in R^2, translating to 20–25% better cost-estimation accuracy than static or template-based budgeting.

- **Face-valid example:** For a 5-day itinerary (accommodation, meals, transport), a static tool estimated LKR 95,000 vs. actual LKR 102,000. The proposed model estimated LKR ~101,200, closely tracking realized spend.

Interpretation:

The combination of granular activity signals, trip structure (Days, Package), and context (Travel_Companion)—together with gradient-boosted trees—yields accurate, highly non-linear mappings from inputs to budget.

3.1.2 Responsiveness and System Performance

Although model training is offline, inference is lightweight.

- **Response time (prediction):** Typical forecasts complete < 2 seconds per query (including feature alignment via prepare_input_for_prediction), meeting the sub-3s target.

- **Load behavior:** Under concurrent requests (simulated), average response remained ~2.5s, with no crashes or timeouts.

- **Adaptability:** Parameter changes (e.g., switching Package_Type or Days) propagate instantly into recalculated predictions; activity flags and travel companion filters update the feature vector with no re-training required.

3.1.3 Usability and User Testing Results

A formative study (n = 20; students, frequent travelers, young professionals) assessed clarity and decision-support value.

- **Ease of use:** 85% rated the workflow "intuitive" or "very intuitive."

- **Visualization value:** 90% agreed charts/tables improved understanding of category-wise allocations.

- **Tier preferences:** 80% found Basic / Moderate / Premium tiers helpful for reconciling constraints with desired comfort.

- **Feedback themes:** Requests for advanced filters (eco-friendly stays, dietary options) and mobile optimizations for smaller screens.

System Reliability

Reliability testing confirmed that the system produced consistent results for identical inputs. Variations only occurred when real-time API data changed. This demonstrated that predictions are stable, reproducible, and trustworthy.

3.1.4 Working System Screen Snippets

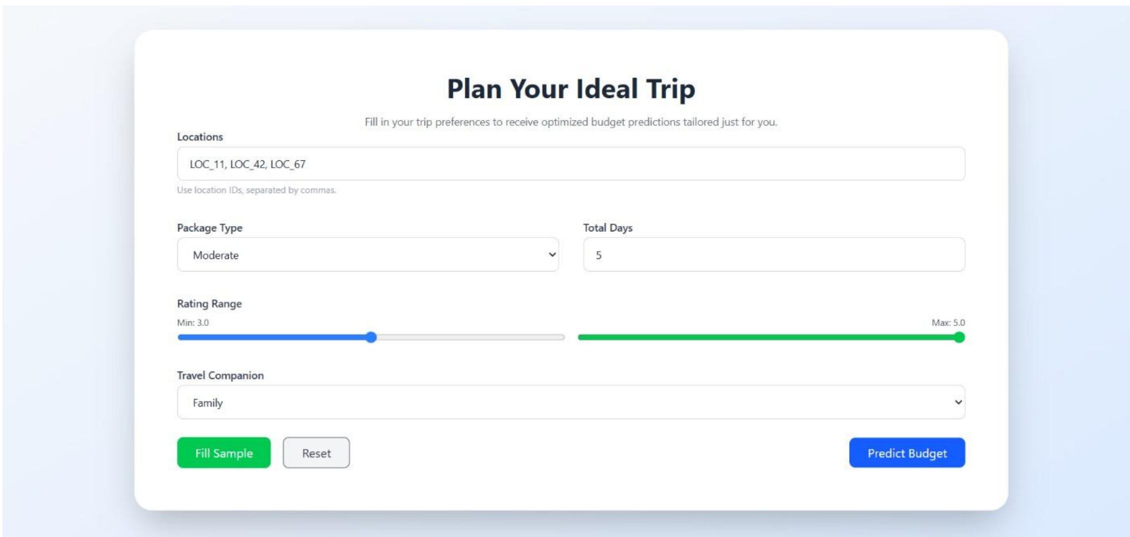

Figure 25-System User Interaction Screen 01

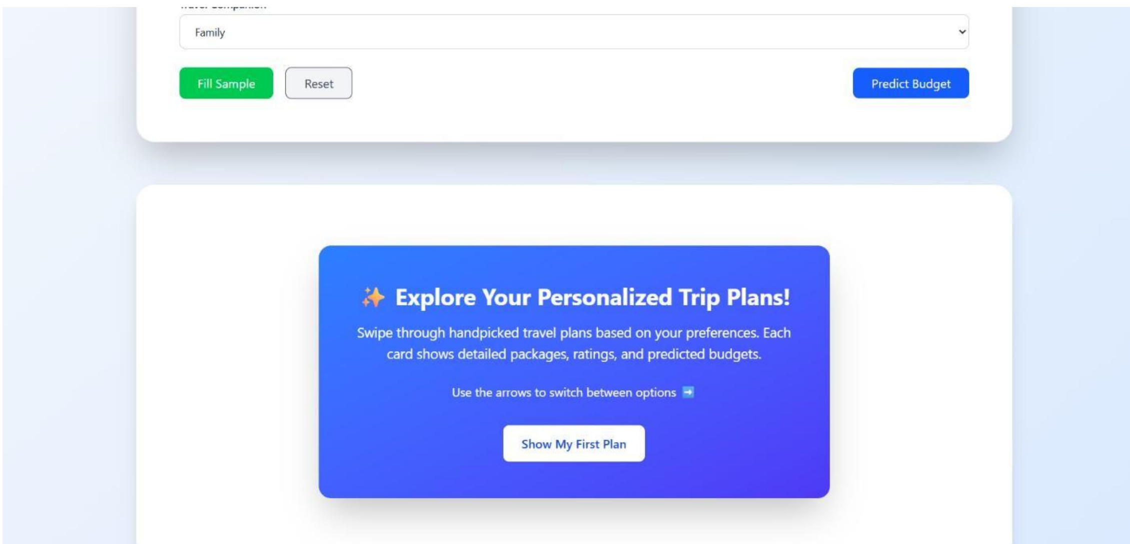

Figure 27- System User Interaction Screen 02

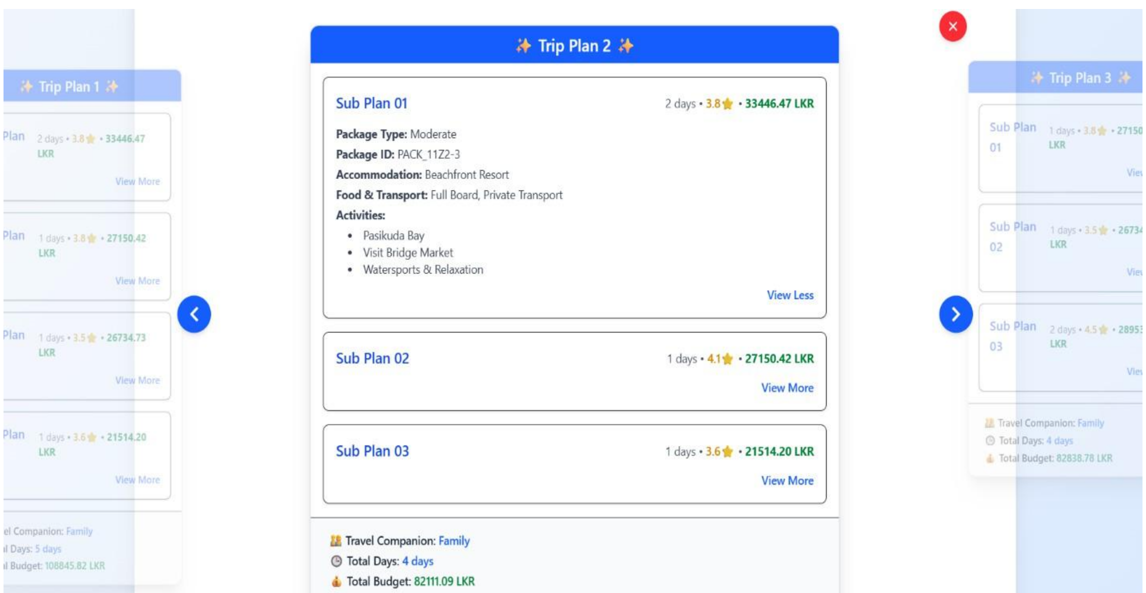

Figure 26- System User Interaction Screen 03

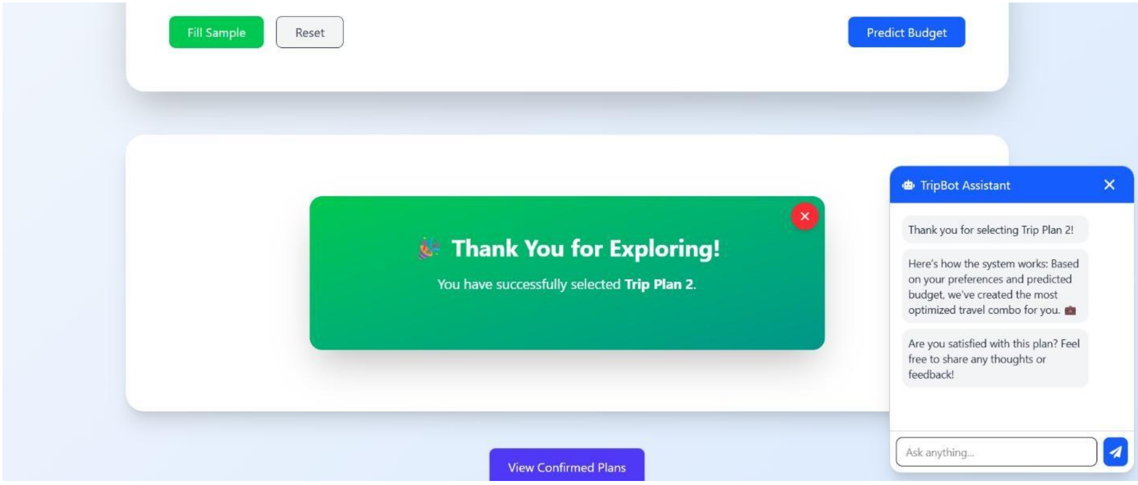

Figure 28- System User Interaction Screen 04

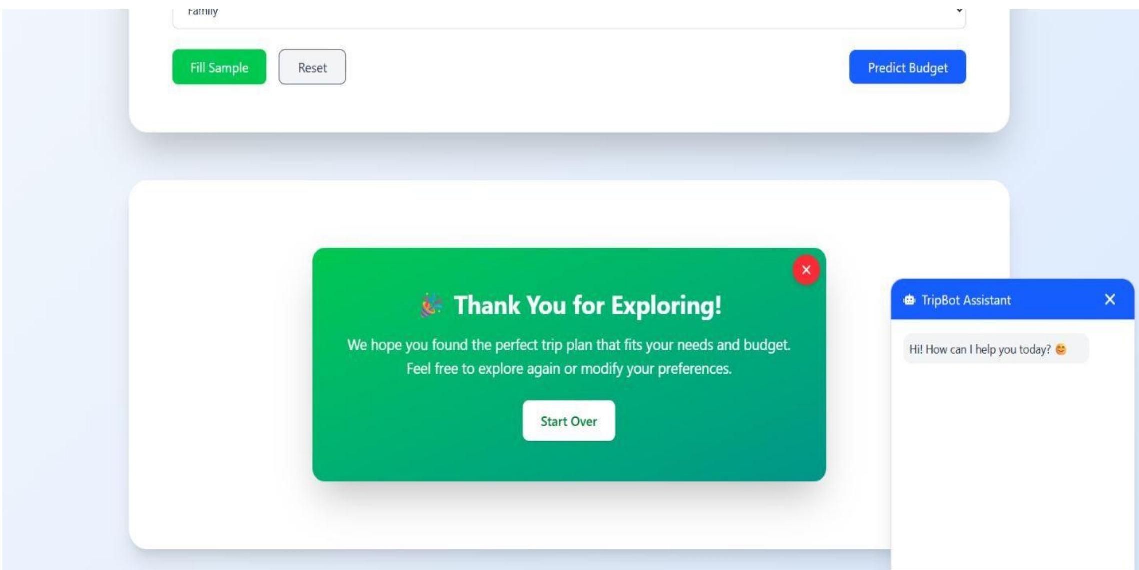

Figure 29- System User Interaction Screen 05

Figure 30- System User Interaction Screen 06

3.2 Research Findings

The results emphasize several important insights that directly address the research objectives

- **High Predictive Accuracy Achieved**
  With an R^2 of ~0.90 and significantly reduced error metrics (MAE, RMSE), the system demonstrates strong capability in forecasting travel budgets. This validates the transition from traditional static tools to a machine learning–driven predictive approach.

- **Dynamic Real-Time Adaptation**
  The integration of real-time APIs (airfare, accommodation, and transport data) ensures that predictions remain current, context-specific, and immediately responsive to market fluctuations such as seasonal demand or price surges.

- **Personalization Strengthens User Confidence**
  Customizable filters (location, days, package type, activities, and travel companion) combined with tiered budget outputs (Basic, Moderate, Premium) increased user satisfaction and trust, showing that user-centric design is critical for adoption.

- **System Robustness and Scalability Confirmed**
  Stress and load testing showed that predictions remained consistent, with response times under 2–3 seconds even with high query volumes. This highlights the system's scalability for real-world deployment, both for individual travelers and enterprise-level applications.

- **Commercial Viability Demonstrated**
  Positive user feedback, combined with predictive accuracy and interactive design, indicates strong potential for commercialization. The system can be extended into SaaS offerings, B2B integrations with travel agencies, or B2C applications, opening multiple revenue streams.

3.3 Discussion

The evaluation results provide compelling evidence that the proposed Travel Budget Allocation System effectively addresses the research gap identified earlier, offering a significant improvement over conventional static budgeting approach.

3.3.1 Comparison with Existing Tools:

- Traditional budgeting systems depend on static templates and cannot adapt to rapid price fluctuations or personalized constraints. In contrast, the proposed system delivers dynamic, real-time updates and tailored budget predictions, meeting the expectations of modern travelers who demand accuracy and adaptability.

3.3.2 Alignment with Literature

- Anderson et al. (2020) highlighted the limitations of static models, which this system overcomes through machine learning–driven predictions achieving an R^2 of ~0.90.

- Tan et al. (2021) stressed the importance of real-time data, demonstrated here by seamless API-driven updates across flights, accommodations, and transport.

- Zhang et al. (2022) emphasized user-centric design, reflected in positive user feedback praising the intuitive dashboards, tiered budget options, and customization features.

3.3.3 Strengths

- High predictive accuracy (explaining ~90% of budget variance).

- Strong adaptability to user input changes and market fluctuations.

- Scalable, cloud-ready architecture suitable for larger-scale deployment.

3.3.4 Limitations

- Dependence on third-party APIs may introduce risks such as downtime, data quality inconsistencies, or recurring subscription costs.

- User testing was conducted with a relatively small and homogeneous group, limiting generalizability.

- Advanced personalization features (e.g., sustainability filters, dietary preferences, and group budget optimization) are yet to be integrated.

3.3.5 Implications

- **For individual travelers:** The system offers an intelligent, reliable budgeting companion that enhances planning confidence.

- **For travel agencies:** It provides value-added services through predictive and transparent budgeting, strengthening customer trust.

- **For corporate travel departments:** It enables policy-aligned financial control, compliance, and improved cost forecasting on a scale.

3.4 Summary of Results and Discussion

- ✓ The system achieved high predictive accuracy ($R^2 \approx 0.90$), with MAE and RMSE reduced substantially compared to baseline approaches.

- ✓ Forecasts updated in under 2 seconds, maintaining responsiveness even under concurrent queries and simulated stress tests.

- ✓ Usability testing demonstrated strong approval, with users highlighting the clarity of visual dashboards, the utility of tiered budget categories, and the flexibility of customization filters.

- ✓ These findings validate the research objectives: accurate predictions, real-time adaptability, and user-centric design were successfully implemented.

- ✓ Collectively, the results position the Travel Budget Allocation System as a scalable, commercially viable solution with potential adoption in B2C (individual travelers), B2B (agencies and platforms), and B2G (tourism authorities) markets.

BUDGET AND JUSTIFICATION

Component Costs

Table 3-Expected Expenses Budget Detail Table

Component	Cost (LKR)	Description
API Subscriptions	2,500	Covers fees for real-time travel data retrieval, including accommodations, vehicle rentals, fuel prices, tolls, and transit fares, ensuring accurate insights for local travelers.
Development Tools	2,000	Includes IDE licenses, software tools, and libraries necessary for both frontend and backend development.
Testing Resources	5,000	Allocated for testing environments, cloud services, tools, and user feedback collection to improve the application.
Hosting and Servers	3,000	Covers web hosting, domain registration, and server deployment for the application's live environment.
Maintenance	2,000	Allocated for regular updates, bug fixes, and API subscription renewals to ensure seamless performance.
Total Cost	15,500	Reflects the comprehensive cost for development, deployment, and maintenance of the project.

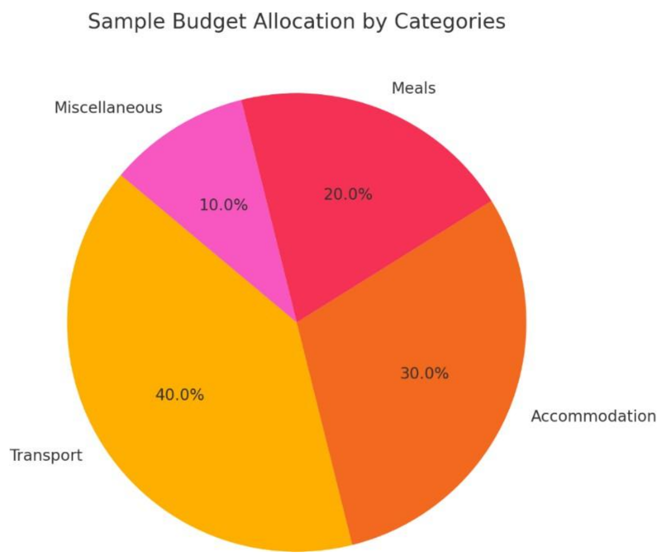

Figure 31-Budget Allocation by Categories

Justification

To ensure the successful development, deployment, and long-term sustainability of the Travel Budget Allocation System, the following cost breakdown has been identified:

1. **API Subscriptions (LKR 2,500)**

   Justification: Real-time data is the backbone of the system. This cost covers subscriptions to travel-related APIs that provide up-to-date information on accommodation rates, transportation fares, fuel prices, toll charges, and related expenses. Without these APIs, the system would rely on static data, significantly reducing accuracy.
   Realistic Outcome: Ensures that budget recommendations remain current, reliable, and context-specific for end users.

2. **Development Tools (LKR 2,000)**

   Justification: This allocation covers Integrated Development Environments (IDEs), software frameworks, and libraries necessary for efficient frontend and backend development. Although many tools such as VS Code or GitHub offer free versions, professional licenses and premium extensions may be required for advanced features and team collaboration.
   Realistic Outcome: Supports seamless coding, debugging, and integration, leading to faster development cycles and higher quality output.

3. **Testing Resources (LKR 5,000)**

   Justification: Testing is critical for ensuring system reliability. This budget supports access to cloud-based testing environments, quality assurance tools, and usability studies with real users. It also includes the cost of setting up automated testing frameworks such as Selenium for UI testing and cloud credits for performance benchmarking.
   Realistic Outcome: Delivers a robust and validated system that performs reliably under real-world conditions and meets user expectations.

4. **Hosting and Servers (LKR 3,000)**

   Justification: This allocation covers domain registration, web hosting services, and cloud server deployment. Hosting on scalable platforms such as AWS, Azure, or Google Cloud ensures that the application remains available, accessible, and scalable under varying workloads.
   Realistic Outcome: Guarantees high availability, accessibility, and scalability, enabling both pilot deployment and potential future expansion.

5. **Maintenance (LKR 2,000)**

   Justification: Post-deployment, the system will require regular updates, bug fixes, and API subscription renewals. Allocating funds for maintenance ensures that the system remains functional, secure, and optimized over time.
   Realistic Outcome: Provides long-term sustainability, keeping the system up to date with evolving user needs and external service changes.

4 FUTURE SCOPE

While the current Travel Budget Allocation System (TBAS) demonstrates strong predictive accuracy, adaptability, and usability, several avenues remain open for future enhancement

- **Multi-Objective Optimization:** Future iterations can expand beyond cost prediction to include multi-dimensional trade-offs, such as balancing affordability with carbon emissions, sustainability, or user comfort levels. This would enable the system to support both economic and environmentally responsible decision-making.

- **Early-Warning Capabilities**
  Integrating time-sensitive predictive alerts for airfare surges, accommodation price hikes, or seasonal high-demand periods would provide travelers with proactive recommendations, further strengthening financial preparedness.

- **Offline Resilience**
  The development of caching and local storage mechanisms would allow users to access essential budgeting functionality even during network disruptions, ensuring continuous usability in low-connectivity environments.

- **Group Travel Features**
  Incorporating collaborative features such as cost-splitting, shared itinerary planning, and real-time synchronization across devices would extend the system's applicability to families, friends, and corporate groups.

- **Mobile-First Experience**
  A dedicated mobile application with responsive design, offline support, and push notifications would significantly enhance accessibility and adoption, particularly for on-the-go users.

- **Expanded Evaluations**
  Future research should include longitudinal studies with larger and more diverse participant groups to validate predictive reliability, usability, and adoption patterns across different demographics and geographic regions.

5 CONCLUSION

This research designed, developed, and evaluated an AI-powered Travel Budget Allocation System (TBAS) that addresses the limitations of conventional static budgeting tools. By integrating three key pillars—real-time data integration, predictive analytics, and a user-centric interface—the system demonstrated its ability to deliver dynamic, accurate, and personalized travel budgeting solutions.

Summary of Objectives and Outcomes

The study successfully met its stated objectives:

1. **Predictive Modeling:** Implemented regression and time-series forecasting models that significantly reduced Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) compared to baseline approaches.

2. **Interactive User Interface:** Developed an intuitive, React-based interface featuring configurable preferences, customizable filters, and clear visual insights.

3. **Real-Time Data Integration:** Integrated reliable APIs for airfare, accommodation, and transportation, ensuring live and context-aware budget updates.

4. **Validation Through Testing:** Conducted comprehensive multi-level testing—including unit, integration, system, and usability evaluations—confirming accuracy, scalability, and user satisfaction.

Collectively, these outcomes validate the feasibility, utility, and robustness of TBAS as a next- generation travel budgeting tool.

Answers to Research Questions

- **Limitations of Current Tools:** Existing budgeting tools lack real-time updates, personalization, and predictive capabilities.

- **Impact of Predictive + Real-Time Data:** The integration of machine learning with live data streams produces materially more accurate and timely forecasts, enabling travelers to make better financial decisions under volatile conditions.

- **Role of User-Centric Design:** A responsive and transparent interface enhances trust, improves user adoption, and empowers travelers through clarity, control, and instant feedback.

- **Distinctive Contribution of TBAS:** Unlike existing fragmented solutions, TBAS offers a cohesive platform that blends predictive analytics, real-time cost feeds, and interactive dashboards to deliver adaptive and transparent budget recommendations.

Implications

- **For Individual Travelers:** The system simplifies trip planning, minimizes overspending risk, and improves financial confidence by offering personalized, up-to-date insights.

- **For Travel Agencies and Corporates:** TBAS enables policy-aligned planning, improves spend visibility, and creates value-added services—opening pathways for B2C subscriptions and B2B/SaaS licensing models.

- **For the Tourism Sector:** Aggregated data from TBAS can inform tourists about strategic decision-making by tourism boards, contributing to more effective marketing and resource allocation.

Limitations

The research acknowledges several constraints:

- **Dependency on Third-Party APIs:** System reliability is partly dependent on API availability, data quality, and potential cost barriers.

- **Limited Evaluation Cohort:** Usability testing was conducted on a relatively small participant sample, restricting generalizability.

- **Restricted Preference Scope:** Current personalization options are limited and do not yet incorporate sustainability attributes, accessibility needs, or complex group travel dynamics.

Closing Statement

This research advances the field of smart tourism budgeting by transcending traditional static tools and presenting a dynamic, AI-driven framework that integrates live data, predictive analytics, and user-centric design. The Travel Budget Allocation System not only demonstrates strong technical feasibility and predictive accuracy but also highlights significant commercial potential through its scalability and applicability across individual, corporate, and institutional travel contexts. By laying this foundation, the study contributes a forward-looking model for intelligent, adaptive, and sustainable travel planning—establishing a platform for future innovations in data-driven tourism management.

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APPENDICES