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Travel Genie: An Intelligent End-to-End Travel and Itinerary Planning System

Gollapalli Akshitha[1], Dr. V. Uma Rani[2]
[1]*Post Graduate Student, M. Tech (Data Science), Department of Computer Science and Engineering, Jawaharlal Nehru Technological University, Hyderabad, India*
[2]*Professor, Department of Computer Science and Engineering, Jawaharlal Nehru Technological University, Hyderabad, India*

Abstract**: Travel itinerary planning is a complex optimization problem that requires balancing multiple factors such as budget, trip duration, accommodation preferences, attraction categories, transportation accessibility and user interests. While existing travel planning systems can generate personalized itineraries, they often lack a comprehensive optimization framework that simultaneously considers geographical proximity, user preferences. To address this challenge, this paper presents Travel Genie, an intelligent travel and itinerary system designed to generate intelligent and personalized travel itineraries for tourists visiting London. The proposed framework integrates clustering and optimization techniques including K-Means Clustering, Constraint Satisfaction Problem (CSP), Mixed Integer Linear Programming (MILP) and Genetic Algorithm (GA) to generate feasible and personalized travel itineraries. User preferences including trip type, budget, group size, trip duration, preferred attraction categories and accommodation requirements are collected through an interactive interface. K-Means clustering groups geographically similar Points of Interest (POIs) to reduce travel complexity, while CSP filters infeasible travel options based on user-defined constraints. MILP then selects an optimal set of attractions that maximizes itinerary quality while satisfying all constraints. Finally, the Genetic Algorithm enhances itinerary diversity and minimizes unnecessary travel between attraction clusters. The generated itineraries are organized into daily schedules with recommended accommodations, nearby transportation information and time-slot allocation for each Point of Interest through a user-friendly Streamlit interface. Experimental evaluation demonstrates the effectiveness of the proposed framework in generating feasible and personalized itineraries with improved clustering quality, high constraint satisfaction and efficient itinerary optimization. The proposed approach provides an effective decision-support system for automated travel planning and enhances the overall travel experience through intelligent itinerary generation.

Keywords**: Travel Itinerary, Points of Interest, Constraint Satisfaction Problem, Mixed Integer Linear Programming, Genetic Algorithm

I. INTRODUCTION

Tourism has become one of the most significant sectors worldwide, with millions of travellers visiting different destinations each year. Planning a trip involves selecting suitable attractions, arranging accommodation, managing transportation and ensuring that all these activities fit within the available budget and time constraints. As the number of available travel options continues to grow, creating an efficient and personalized itinerary has become increasingly complex.

Traditional travel planning methods require travellers to manually search for attractions, compare accommodations and organize daily schedules. This process is often time-consuming, inefficient and often results in suboptimal itineraries that do not fully satisfy user preferences. In addition, travellers may overlook important attractions or spend excessive time travelling between locations which may make them not cover as many POIs as they wished for.

To address these challenges, this paper proposes Travel Genie, an intelligent travel and itinerary planning system that generates optimized and personalized travel itineraries for tourists visiting London. The system considers user preferences including trip type, budget, group size, trip duration, hotel preferences, POI preferences. It combines K-Means Clustering to group geographically related attractions, Constraint Satisfaction Problem (CSP) to eliminate infeasible travel options, Mixed Integer Linear Programming (MILP) to select an optimal set of attractions while satisfying user-defined constraints and Genetic Algorithm to further improve itinerary quality and attraction diversity. The generated itineraries are organized into day-wise schedules with recommended accommodations, nearby transportation information and allocated time slots for each selected POI. A user-friendly Streamlit interface enables travellers to efficiently generate personalized travel plans without requiring extensive manual planning.

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The proposed system aims to reduce travel planning effort, improve itinerary quality and provide personalized recommendations by integrating clustering and optimization techniques within a unified framework. By combining Artificial Intelligence, Machine Learning and mathematical optimization, Travel Genie offers an intelligent decision-support system that generates feasible, efficient and user-centric travel itineraries.

II. LITERATURE REVIEW

Recent advances in the technologies like Artificial Intelligence, Machine Intelligence and optimization techniques have significantly improved personalized travel recommendation and itinerary planning systems. Early research primarily focused on recommending individual Points of interest (POIs), while more recent studies have attempted to generate complete travel itineraries by considering user preferences, travel constraints and contextual information.

Chang et al. [1] proposed a personalized travel itinerary recommendation framework that integrates Matrix Factorization and ResNet-based visual feature extraction to model user interest from geo-tagged Flickr images. The itinerary planning problem is formulated as an Orienteering Problem and solved using an Iterated Local Search with Adaptive Perturbation (ILSAP) algorithm to maximize tourist satisfaction while considering travel time, POI popularity and route constraints. Experimental results demonstrates superior performance compared with heuristic, collaborative filtering and deep learning based recommendation approaches.

Li et al. [2] introduced a personalized trip itinerary planning framework based on a Contextual Multi-Armed Bandit (CMAB) model. Their approach considers contextual information such as travel season, hotel location, user preferences and attraction ratings to recommend personalized itineraries. K-Means clustering is employed to identify attraction-rich regions, while different exploration strategies are evaluated against an Adaptive Genetic Algorithm. Although the proposed system improves personalization, it primarily relies on reward-based learning and provides limited support for explicit constraint handling.

Prabha et al. [3] developed a Personalized Travel Itinerary Generator System that combines Restricted Boltzmann Machines, Alternating Least Squares and Hybrid Recommendation Models to generate customized travel itineraries. Their framework recommendation model enhances personalization, the itinerary generation process is primarily recommendation-driven and does not explicitly optimize travel constraints.

Ho and Lim [4] introduced POIBERT, a Transformer-based itinerary recommendation model that formulates itinerary generation as a sequence prediction problem. By learning historical travel trajectories form geo-tagged Flickr data, the model predicts successful POIs using the BERT architecture while considering travel time and visit duration. Experimental evaluation demonstrated that POIBERT consistently outperformed traditional sequence prediction methods in terms of Precision, Recall and F1-score.

Although recent studies have significantly advanced personalized travel planning through recommendation systems, deep learning models, contextual learning, and optimization heuristics, most existing approaches either emphasize recommendation quality or focus on a limited set of optimization objectives. Explicit integration of geographical clustering, constraint satisfaction, mathematical optimization, and itinerary refinement within a unified framework remains limited. To address this research gap, the proposed Travel Genie framework combines K-Means Clustering, Constraint Satisfaction Problem (CSP), Mixed Integer Linear Programming (MILP), and a Genetic Algorithm (GA) to generate feasible, optimized, and personalized travel itineraries while simultaneously considering user preferences, budget, trip duration, accommodation requirements, attraction diversity, and transportation accessibility.

III. METHODOLOGY

A. System Architecture

The system architecture of Travel Genie provides a structured framework for transforming user preferences and travel-related data into a personalized and optimized travel itinerary. As illustrated in Figure 1, the framework consists of multiple interconnected modules that collectively perform data preprocessing, user preference analysis, clustering, optimization and itinerary generation.

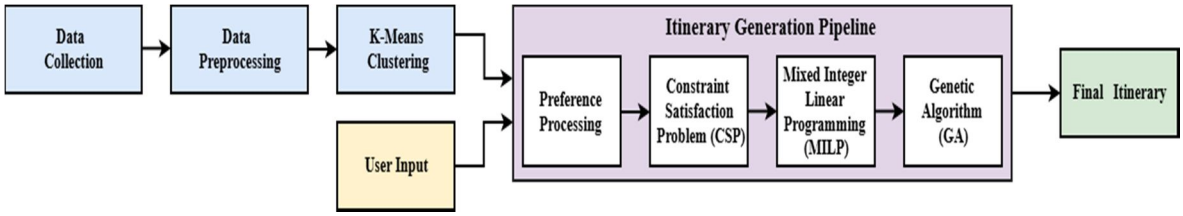


Fig. 1 General Architecture

Initially, travel-related datasets including Points of Interest, hotels and transportation information are collected and preprocessed. User preferences such as trip type, budget, trip duration, accommodation requirements, group size and preferred POI categories are obtained through the Streamlit-based user interface. The preprocessed POIs are then grouped using K-Means Clustering to identify geographically related attractions and reduce travel complexity.

The clustered POIs and processed user preferences are subsequently passed to the itinerary generation framework. A Constraint Satisfaction Problem (CSP) is first employed to eliminate infeasible travel options based on user-defined constraints. Mixed Integer Linear Programming (MILP) then selects an optimal set of attractions while satisfying the specified constraints and a Genetic Algorithm (GA) further refines the itinerary by improving attraction diversity and reducing unnecessary travel between locations.

Finally, the system generates a personalized day-wise itinerary containing the selected attractions, recommended accommodations (if requested), nearby transportation information and allocated time slots for each selected POI providing travellers with an efficient and practical travel plan.

B. Dataset Description

The proposed framework utilizes three datasets comprising tourist attractions, hotels and transportation facilities in London. The POI dataset is used for attraction clustering and itinerary generation, the hotel dataset is used for accommodation recommendation and transportation dataset provides nearby transit information. During preprocessing, only the attributes relevant to itinerary generation and optimization were retained.

TABLE I
SUMMARY OF DATASETS USED

Dataset	Source	Size	Purpose	Key Features
POI	OpenStreetMap Overpass API	903 records	Attraction selection	Name, category, Coordinates, Opening Hours
Hotel	Inside Airbnb London	80984 records	Accommodation recommendation	Name, Price, Rating, Capacity, Coordinates
Transportation	OpenStreetMap Overpass API	20615 records	Nearby transport recommendation	Transport Type, Name, Coordinates

C. Proposed Framework

1) Data Preprocessing

The data preprocessing stage prepares the collected datasets for subsequent clustering and optimization. Missing values are handled, duplicate records are removed, category names are standardized and geographical coordinates are validated to ensure data consistency. Feature engineering is also performed to derive meaningful attributes from the hotel dataset, improving hotel recommendation and selection. The resulting datasets provide reliable and structured inputs for the itinerary generation framework.

2) K-Means Clustering

K-Means Clustering is employed to partition geographically similar POIs into k clusters using their latitude and longitude coordinates. The algorithm minimizes the within-cluster sum of squared distances between POIs and their corresponding cluster centroids, as expressed by

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2$$

where,

C_i represents the ith cluster and μ_i denotes its centroid. In the proposed framework, clustering reduces the search space for itinerary generation and minimizes travel distance by grouping nearby attractions.

3) Constraint Satisfaction Problem

The Constraint Satisfaction problem (CSP) is used to identify feasible travel options before optimization. A CSP consists of variables, domains and constraints:

$$CSP = (X, D, C)$$

where,

$X = \{x_1, x_2, x_3, \ldots x_n\}$ represents the set of decision variables

$D = \{d_1, d_2, d_3, \ldots d_n\}$ denotes the corresponding domains of the variables

$C = \{c_1, c_2, c_3, \ldots c_n\}$ denotes the set of constraints that must be satisfied

In the proposed system, the decision variables correspond to candidate POIs and hotel selections, while the domains represent the feasible travel options available for each variable. The constraints include user-defined budget, trip duration, trip type, accommodation requirements, preferred attraction categories, attraction operating hours and accessibility conditions. For users requesting accommodation, the CSP identifies feasible hotel-POI combinations based on proximity and accessibility. For users who do not require accommodation, only attraction-related constraints are enforced. Consequently, only feasible travel options satisfying all constraints are forwarded to the MILP optimization stage, thereby reducing the search space and improving computation efficiency.

4) Mixed Integer Linear Programming

The Mixed Integer Linear Programming (MILP) model is employed to determine the optimal itinerary from the feasible solutions generated by the CSP. MILP formulates itinerary planning as a mathematical optimization problem by maximizing the overall itinerary quality while satisfying multiple linear constraints.

The objective function is defined as

$$\max Z = \sum_{i=1}^{n} S_i x_i$$

where,

Z is the objective function value,

S_i is the score of the i^{th} POI,

x_i is a binary decision variable (1 if the POI is selected, 0 otherwise),

n represents the total number of feasible POIs

The MILP model identifies the optimal combination of attractions that maximizes user satisfaction while ensuring that all specified constraints are satisfied. The optimized itinerary generated by the MILP model is subsequently refined using the Genetic Algorithm.

5) Genetic Algorithm

The Genetic Algorithm (GA) is employed to further improve the itinerary generated by the MILP optimization stage. GA is an evolutionary optimization technique that iteratively refines candidate solutions using the principles of natural selection, crossover and mutation.

Each chromosome represents a complete travel itinerary, while the fitness of each chromosome is evaluated using

$$\text{Fitness} = f(D, Q, C)$$

where,

D represents attraction diversity,

Q denotes itinerary quality,

C represents cluster distribution and travel efficiency

During each generation chromosomes with higher fitness values are selected for reproduction. Crossover combines high-quality itinerary segments from parent chromosomes, while mutation introduces small variations to maintain population diversity and prevent premature convergence. Through successive generations, the GA improves attraction diversity, minimizes unnecessary travel between attraction clusters and enhances the overall quality of the itinerary. The chromosome with the highest fitness values is selected as the final optimized itinerary.

6) Optimized Day-wise Itinerary

The optimized itinerary generated by the Genetic Algorithm is organized into a structured day-wise travel schedule. The selected Points of Interest (POIs) are arranged according to their cluster assignments, travel sequence, and allocated visit time slots to minimize unnecessary travel and improve itinerary efficiency. The scheduling process ensures that the selected attractions satisfy the user-defined constraints, including trip duration, preferred attraction categories, and attraction operating hours.

For users requesting accommodation, the itinerary includes a recommended hotel selected during the optimization process. Nearby transportation information is also provided to facilitate convenient travel between attractions.

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The final itinerary presents each day's travel plan in a chronological order, including the recommended attractions, allocated visit time slots, accommodation details (if applicable), and transportation recommendations. The generated itinerary is displayed through a user-friendly Streamlit interface, enabling travellers to interactively explore personalized and optimized travel plans.

D. Evaluation Metrics

1) Silhouette Score

The Silhouette Score evaluates the quality of the clusters generated by the K-Means algorithm by measuring how similar a Point of Interest (POI) is to other POIs within the same cluster compared to those in the nearest neighbouring cluster.

Formula:

For the individual point:

$$S(i) = \frac{b(i)-a(i)}{\max(a(i),b(i))}$$

where,

a(i): Average distance between the i^{th} data point (POI) and all other data points within the same cluster

b(i): Average distance between the i^{th} data point (POI) and all other data points in the nearest neighbouring cluster

S(i): Silhouette score of the i^{th} data point (POI) indicating how well it is assigned to its own cluster compared to the nearest neighbouring cluster

Overall Silhouette Score is,

$$\text{Overall Silhouette Score} = \frac{1}{N}\sum_{i=1}^{N} S(i)$$

where,

N = Total number of data points (POIs) in the dataset.

2) Preferred category Coverage

The Preferred Category Coverage measures the extent to which the generated itinerary includes the attraction categories specified by the user. This metric evaluates how effectively the itinerary satisfies user preferences while maintaining personalization.

Formula:

$$\text{Preferred Category Coverage} = \frac{Preferred\ Categories\ Included}{Preferres\ Categories\ requested} \times 100$$

A higher Preferred Category Coverage indicates that a greater proportion of the user's preferred attraction categories are included in the generated itinerary. This metric evaluates the effectiveness of the Genetic Algorithm (GA) in refining the itinerary to better align with user preferences while maintaining an optimized travel plan.

3) Constraint Satisfaction Rate

The Constraint Satisfaction Rate measures the percentage of user-defined constraints successfully satisfied during itinerary generation.

Formula:

$$\text{Constraint Satisfaction Rate} = \frac{Satisfied\ Constraints}{Total\ Constraints} \times 100$$

A higher Constraint Satisfaction rate indicates that the proposed framework effectively generates feasible itineraries while satisfying constraints such as budget, trip duration, accommodation requirements, attraction preferences and operating hours.

IV. RESULTS

A. Performance evaluation

TABLE II summarizes the quantitative performance of the proposed Travel genie framework. The obtained Silhouette Score of 0.461 indicates good cluster separation for geographical grouping of POIs.

While the Preferred Category Coverage (84%) indicates that the generated itineraries successfully include the majority of the attraction categories specified by the users, demonstrating the effectiveness of the Genetic Algorithm in refining the itinerary according to user preferences while maintaining itinerary quality. Furthermore the Constraint Satisfaction Rate (95%) shows that most user-defined constraints are successfully satisfies during itinerary generation.

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TABLE II
PERFORMANCE EVALUATION OF THE PROPOSED SYSTEM

Evaluation Metric	Observed Value
Silhouette Score	0.461
Preferred Category Coverage	84%
Constraint Satisfaction Rate	95%

B. Experimental Analysis

1) Elbow Method

The elbow method is used to determine the optimal number of cluster for K-Means Clustering. The inertia decreases at k=4 indicating that 4 clusters provide a good clustering quality.

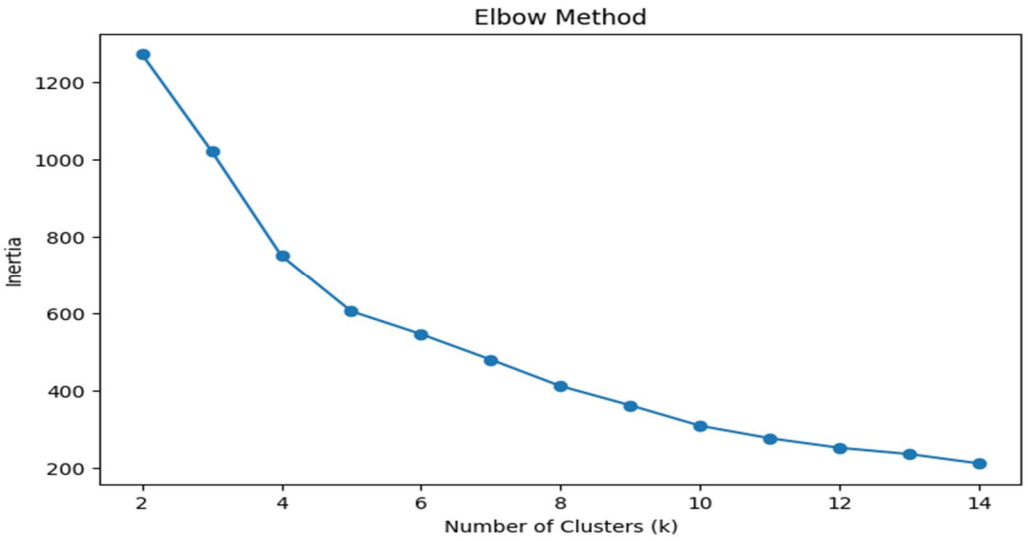


Fig. 2 Elbow Curve for determining optimal number of clusters

2) Silhouette Analysis

The below visualization shows the Silhouette Scores for the different cluster sizes. A high silhouette score of 0.461 at k=4 indicates well-separated and cohesive clusters, supporting the selection of four clusters for POI grouping.

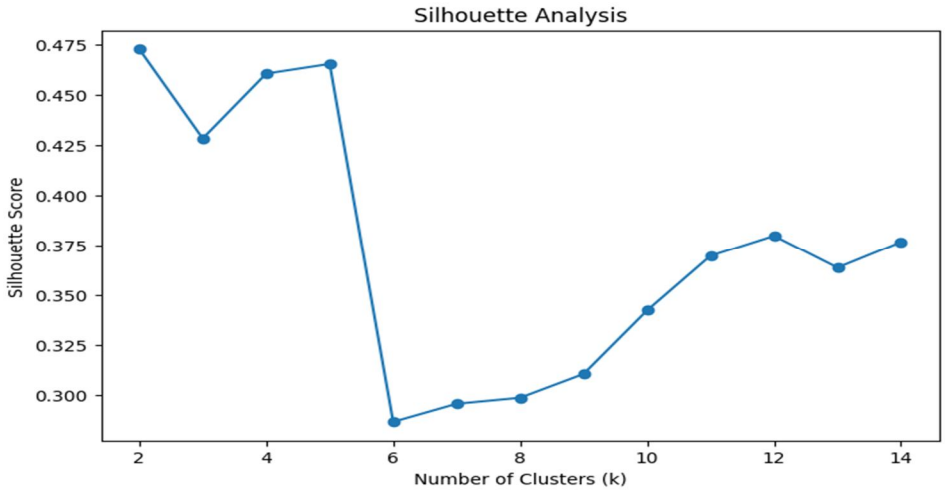


Fig. 3 Silhouette Analysis for K-Means Clustering

3) POI Cluster Visualization

The below visualization illustrates the spatial distribution of Points of Interest (POIs) after applying K-Means Clustering with k=4. Each colour represents a distinct cluster of geographically similar POIs, enabling the system to group nearby attractions and reduce travel distance during itinerary generation.

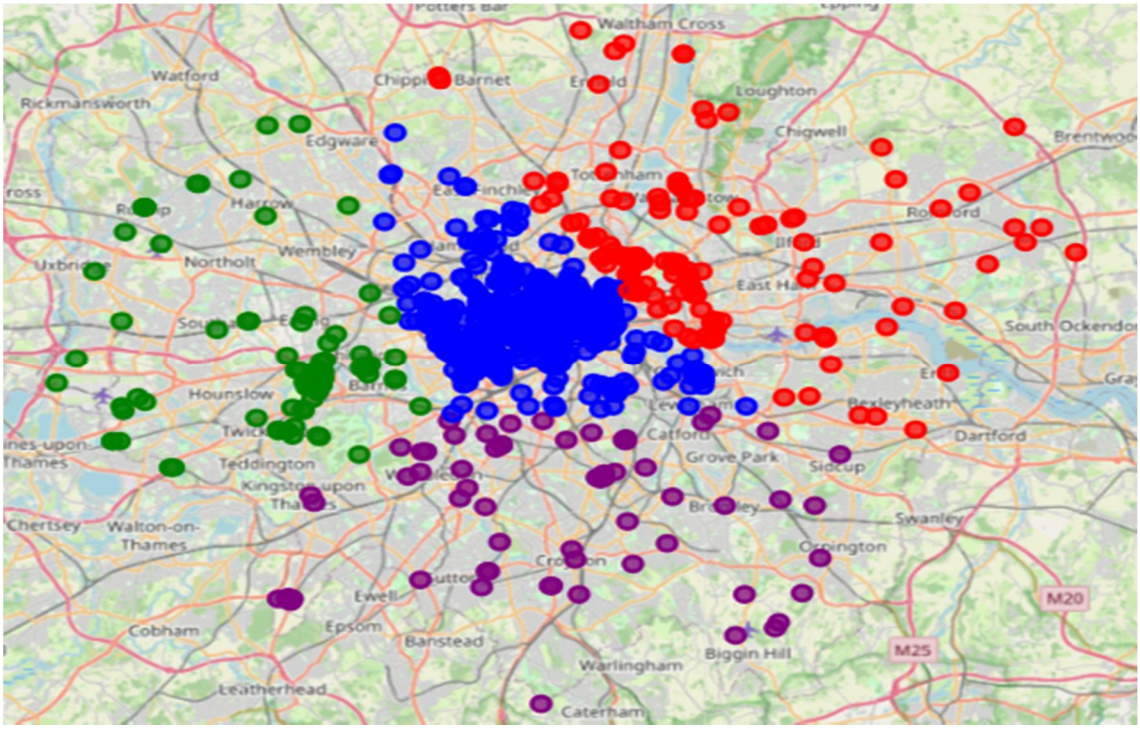


Fig. 4 Spatial Distribution of POIs using K-Means

4) POI Category Distribution

The below figure illustrates the distribution of Points of Interest (POIs) across different tourism categories in the dataset.

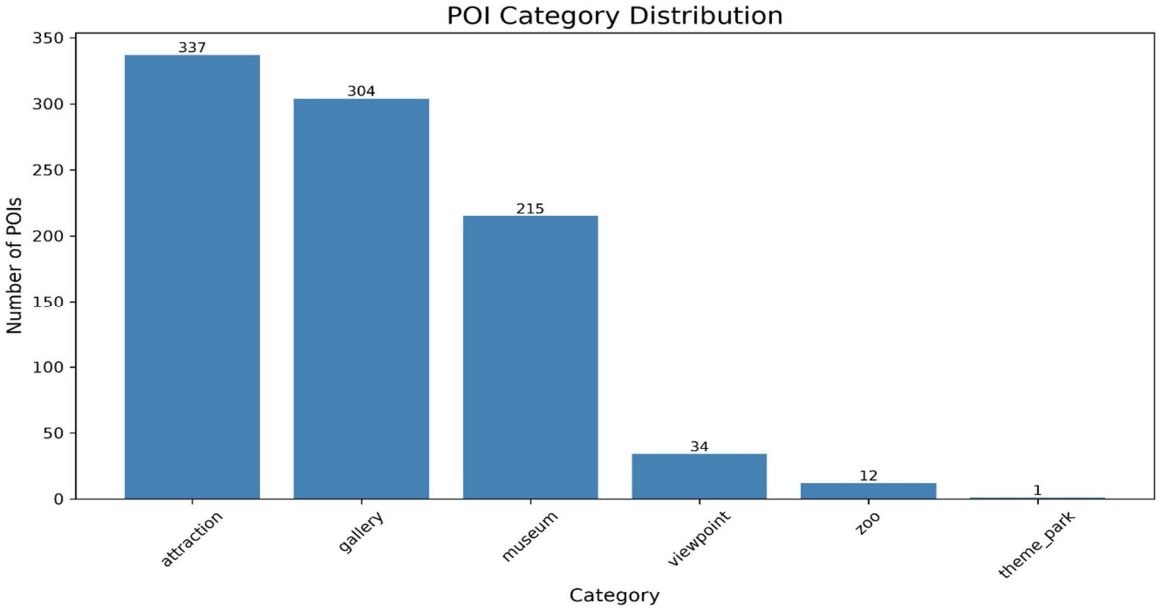


Fig. 5 Distribution of Points of Interest Across Different Categories

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5) Hotel Price Distribution

It illustrates the distribution of hotels across different price ranges in the dataset. Most hotels fall within the £50-100 and £100-150 price ranges, providing a wide range of mid-budget accommodation options for itinerary generation.

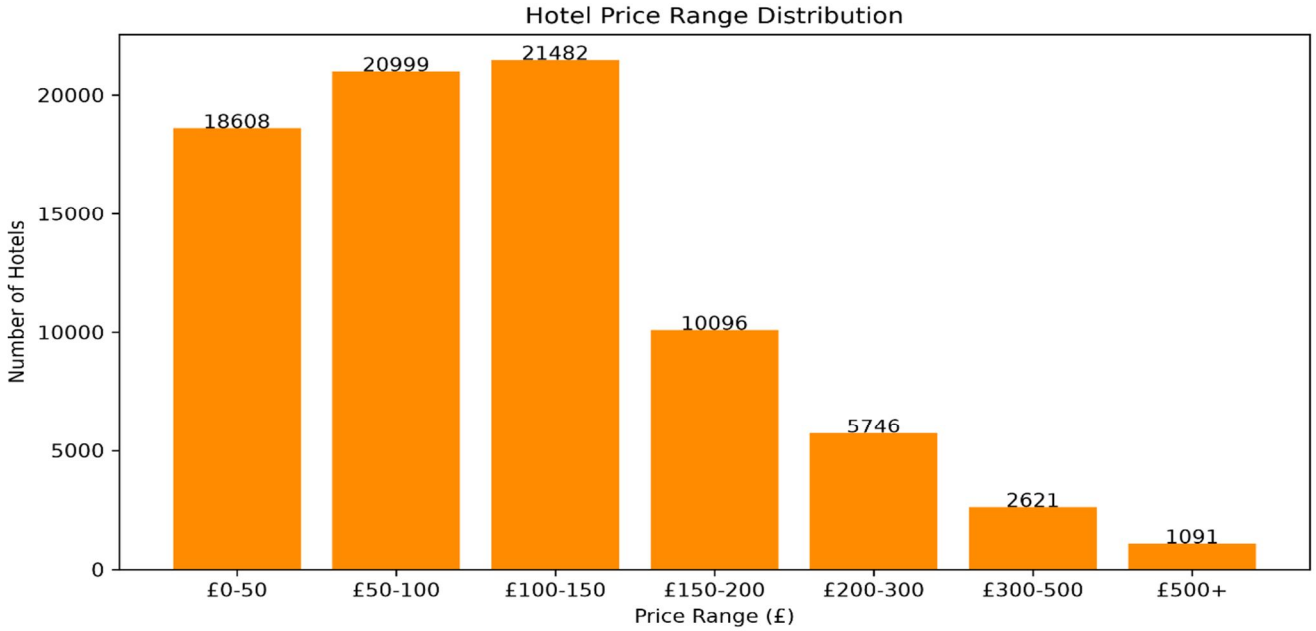


Fig. 6 Distribution of Hotel Prices per Night

C. User Interface and Generated itinerary

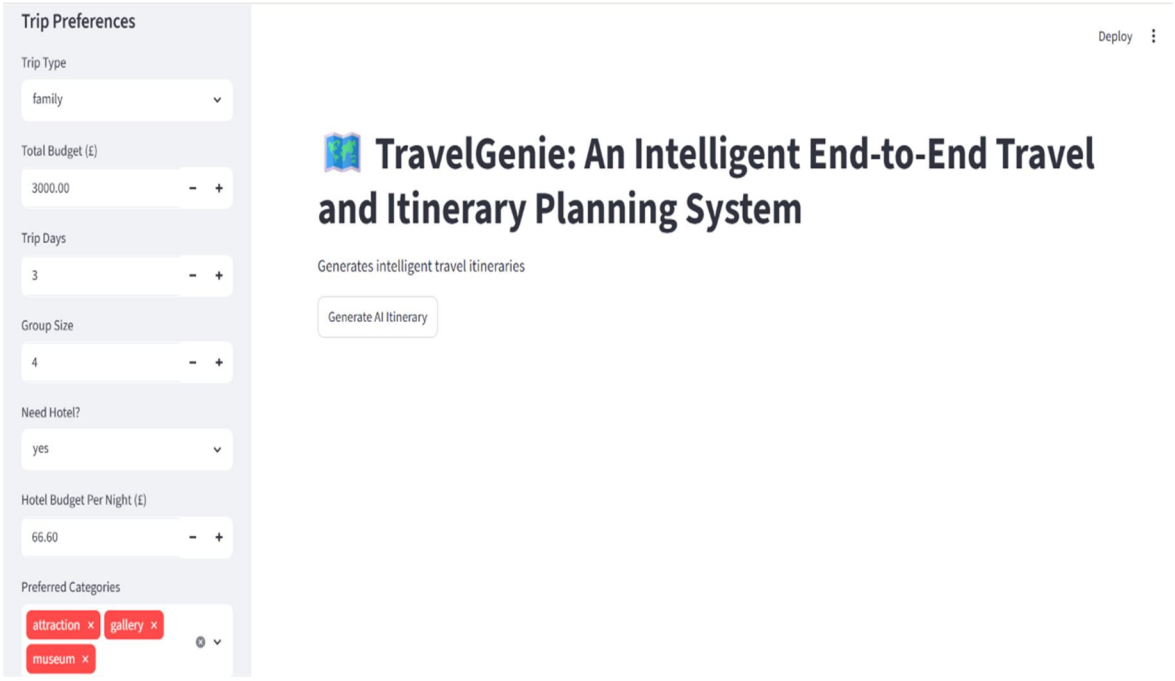


Fig. 7 User Interface of Travel Genie system



Fig. 8(a) Itinerary Generation when hotel is selected

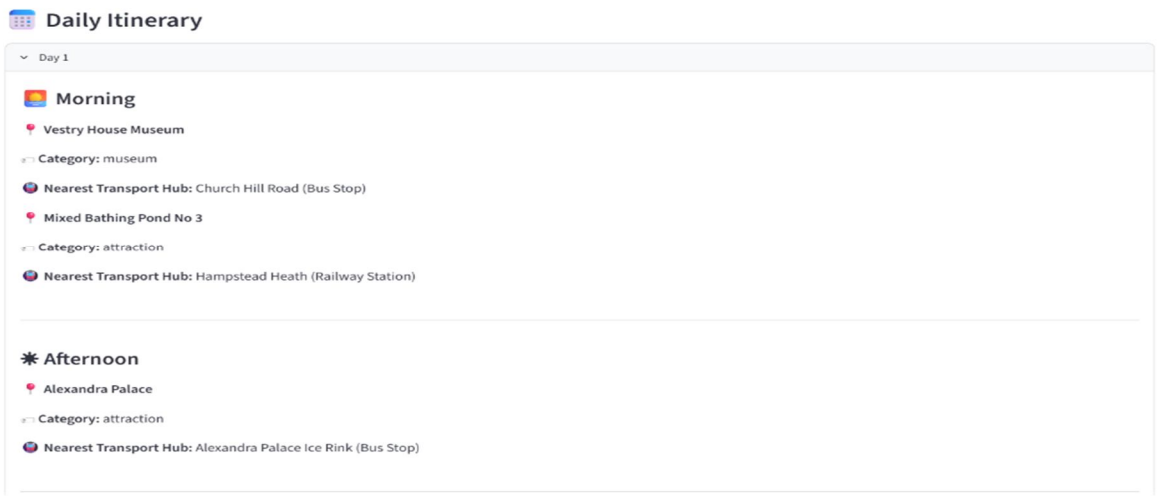


Fig. 8(b) Itinerary Generation when hotel is selected

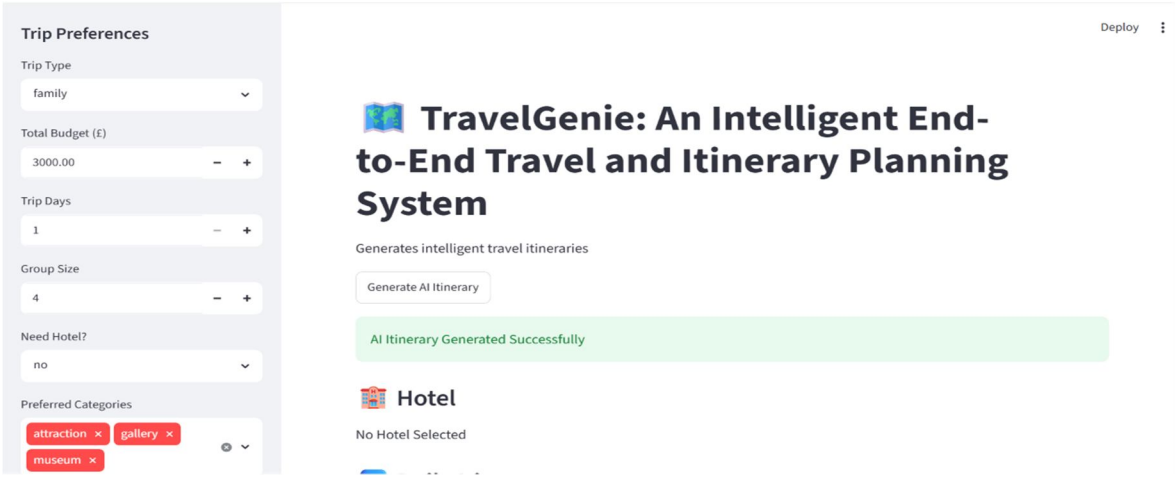


Fig. 9(a) Itinerary generation when hotel is not selected

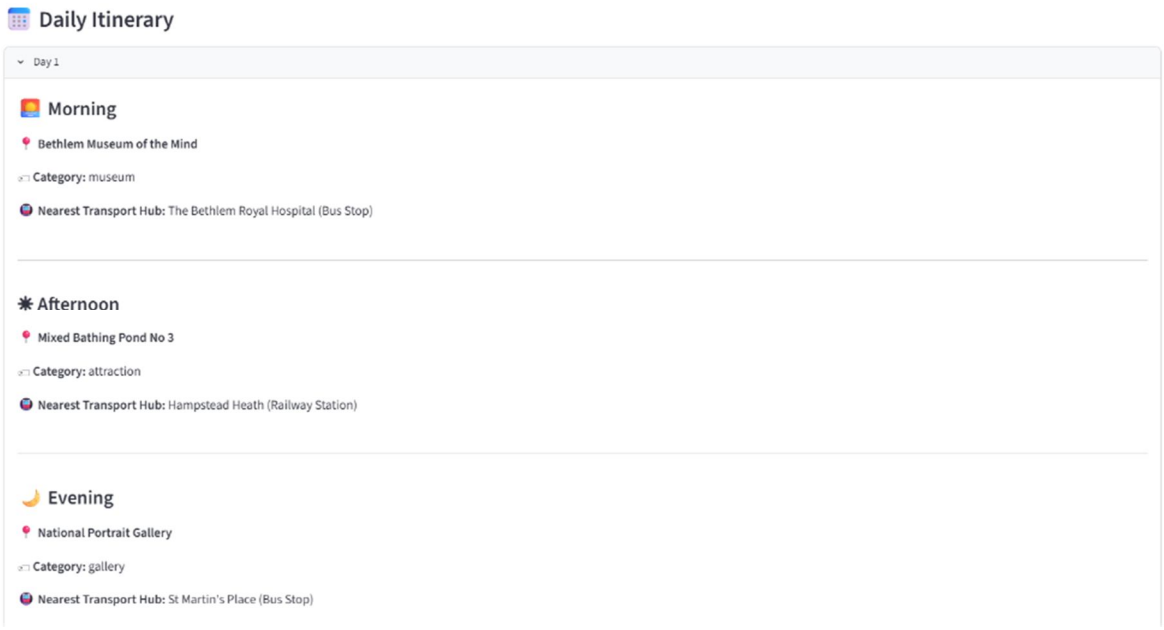


Fig. 9(b) Itinerary generation when hotel is not selected

V. CONCLUSION

This paper presented Travel Genie, an intelligent travel and itinerary planning system that generates personalized and optimized travel itineraries by integrating user preferences, accommodation recommendations, transportation information, and multiple computational techniques within a unified framework. The proposed system combines K-Means Clustering for geographically grouping Points of Interest (POIs), a Constraint Satisfaction Problem (CSP) for identifying feasible travel options, Mixed Integer Linear Programming (MILP) for optimal attraction selection, and a Genetic Algorithm (GA) for refining itinerary quality and attraction diversity. Experimental evaluation using the Silhouette Score, Preferred Category Coverage and Constraint Satisfaction Rate demonstrates the effectiveness of the proposed framework in generating feasible, optimized, and diverse travel itineraries. The results indicate that the system effectively reduces manual travel planning effort while providing personalized, practical, and efficient travel recommendations.

Future work will focus on extending the proposed framework by incorporating real-time traffic, weather, hotel availability, and transportation data to support dynamic itinerary generation. Integration with live hotel booking and flight reservation APIs can further enhance the practicality of the system by enabling real-time cost estimation and booking facilities. Additionally, the framework can be extended to support multi-city and international trip planning, multilingual interaction, and offline navigation capabilities. These enhancements would improve the scalability, adaptability, and real-world applicability of the proposed travel planning system.

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REFERENCES

[1] Chang, C.-W., Tsai, C.-Y., Yao, L., Kuo, R. J., and Tsai, C.-Y., "Personalized Travel Itinerary Recommendation Enhancing by User Interests and Point-of-Interest Characteristics," Information Technology & Tourism, vol. 27, pp. 649–682, 2025, doi: 10.1007/s40558-025-00318-2.

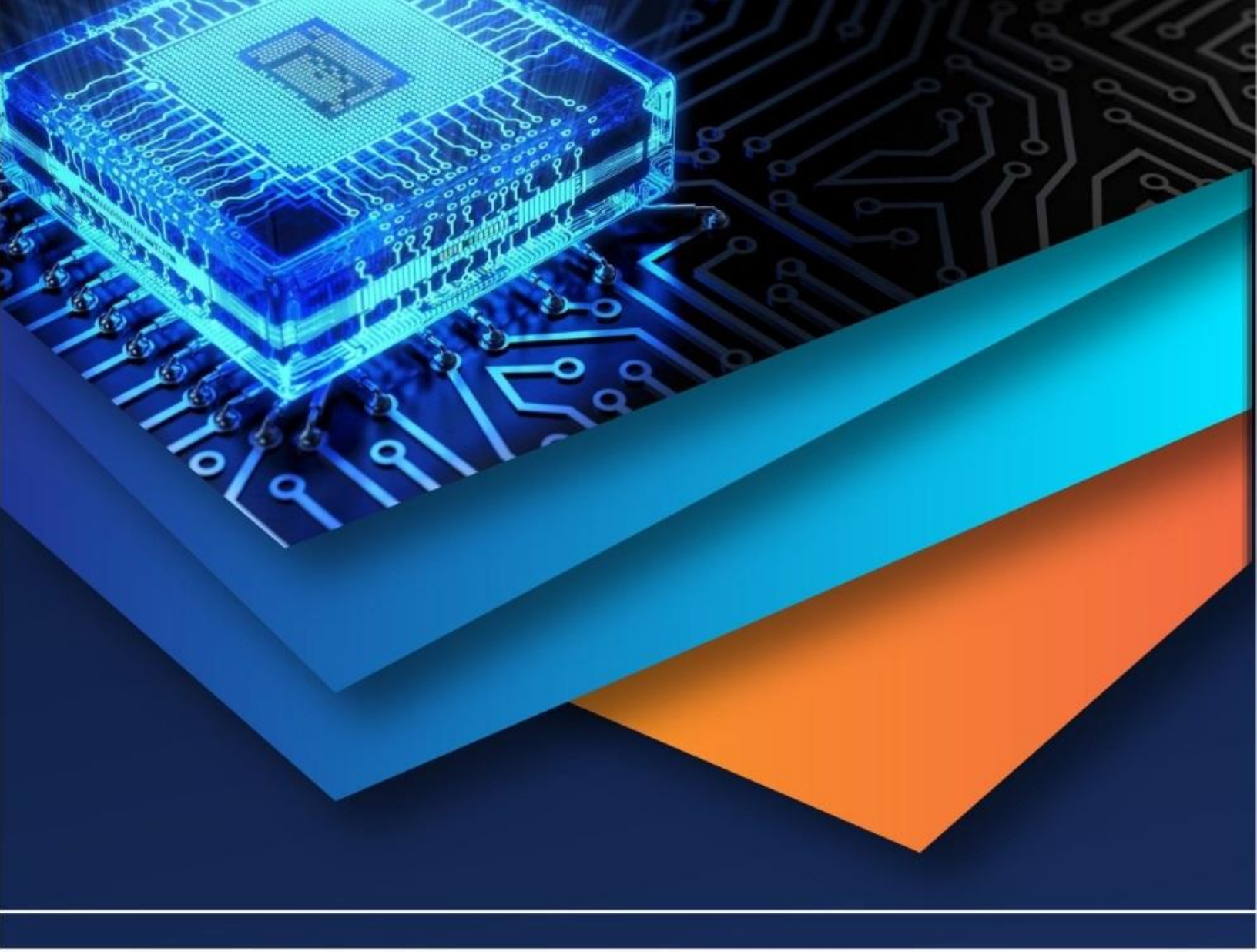
[2] H. Li, M. Wang, J. Zhang, T. Shi, and A. Khamis, "A Contextual Multi-armed Bandit Approach to Personalized Trip Itinerary Planning," in Proc. 2024 IEEE International Conference on Smart Mobility (SM), pp. 55–60, 2024. doi: 10.1109/SM63044.2024.10733530.

[3] N. S. Prabha, G. Kalaiarasi, V. Nivash, M. Selvi, and R. Yogitha, "Personalized Travel Itinerary Generator System," in Proc. 2024 International Conference on Intelligent Systems for Cybersecurity (ISCS), 2024. doi: 10.1109/ISCS61804.2024.10581212.

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[4] T. Ho and A. Lim, "POIBERT: A Transformer-based Model for the Tour Recommendation Problem," in Proc. IEEE International Conference on Big Data (Big Data), 2022, pp. 4935–4944. doi: 10.1109/BigData55660.2022.10020877.
[5] D. Jawale, P. Mishra, P. Kamble, D. Mhatre, S. Jadhav, and L. Singh, "AI-Optimized Itinerary Design: Transforming the Future of Travel Planning," Journal of Artificial Intelligence Research & Advances, vol. 12, no. 2, pp. 74–82, Apr. 2025. doi: 10.37591/JoAIRA.
[6] C. Almira and N. U. Maulidevi, "Travel Itinerary Recommendation for Real World Point of Interests Using Iterated Local Search," in Proc. 2019 International Conference of Advanced Informatics: Concepts, Theory and Applications (ICAICTA), 2019, pp. 1–6, doi: 10.1109/ICAICTA.2019.8904339.
[7] Chen, S. Wu, J. Zhou, and A. K. H. Tung, "Automatic Itinerary Planning for Traveling Services," IEEE Transactions on Knowledge and Data Engineering, vol. 26, no. 3, pp. 514–527, Mar. 2014. doi: 10.1109/TKDE.2013.46.
[8] S. Dhote, N. Gayakwad, P. Buwade, R. Bedre, and P. S. Sisodiya, "AI-Powered Travel Planner: Smart Trip Optimization," International Journal of Leading Research Publication (IJLRP), vol. 6, no. 3, Mar. 2025, E-ISSN: 2582-8010.
[9] A. Gawade, S. Jadhav, P. Patil, R. Khule, and P. K. Mishra, "AI-Powered Personalized Travel Itinerary Planning Using Real-Time Data," International Journal of Scientific Advances and Technology (IJSAT), vol. 2, no. 4, pp. 1–7, 2025.
[10] L. Chen, L. Zhang, S. Cao, Z. Wu, and J. Cao, "Personalized Itinerary Recommendation: Deep and Collaborative Learning with Textual Information," Expert Systems with Applications, vol. 144, Art. no. 113070, 2020. doi: 10.1016/j.eswa.2019.113070.

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