International Journal of Engineering Research and Science & Technology

IJERST

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 2(2) (2026)

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

Hybrid Recommendation Mechanisms for Tourism Personalization: A Computational Study in the Indonesian Context

S. Sankar Ganesh[1*], Kudugunti Raghavendar[2], Shyam Bejjenki[2], Kotla Swaran Kumar[2]

[1]Associate Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering (AI & ML), [1,2]Kommuri Pratap Reddy Institute of Technology, Ghanpur, Ghatkesar, 501301, Telangana, India.

*Correspondence: S. Sankar Ganesh

Abstract

The tourism industry in Indonesia has experienced rapid growth, generating large volumes of data on tourist preferences, destinations, travel costs, and durations. Traditional travel recommendations, provided through agencies or static guidebooks, often rely on generalized assumptions and fail to adapt to individual user preferences. Consequently, tourists frequently receive generic suggestions that may not align with their specific needs, resulting in suboptimal travel experiences. To address these limitations, this study proposes a hybrid learning-based travel recommendation system that leverages Indonesian tourism datasets to deliver personalized suggestions. The system employs multiple Classification and Regression Trees (CART)-based models, including Linear Logistic Regression (LLR), Support Vector Machine (SVM), and Random Forest (RF), for comparative analysis. The primary model, Neuro-Tree-Net, integrates an Artificial Neural Network (ANN) with an Extra Trees (ET) model, combining tree-based learning with neural network-based representation learning to capture complex nonlinear relationships in tourism data. Experimental results demonstrate that the hybrid model outperforms traditional single-model approaches in prediction accuracy. Users can input constraints such as maximum cost, available travel time, and minimum rating preferences to receive personalized destination recommendations. The backend efficiently manages dataset processing, model training, and prediction using libraries including pandas, scikit-learn, Keras, and Matplotlib, while results are presented through a dynamic web interface built with Django. Beyond accurate recommendations, the system supports comprehensive analysis of tourism patterns, enabling travellers to make more informed decisions.

Keywords: Travel Recommendation Systems, Personalized Tourism, Hybrid Learning Models, Neuro-Tree-Net, Tourism Data Analytics.

1. Introduction

In data-driven markets, digital platform competitors reliably offer effective advice. Recommendation engines are a powerful tool for internet companies. While thematic recommendation systems employ deep technologies such as deep and reinforced learning for data streaming in eCommerce applications (platforms such as Spotify, Netflix, and Amazon), other sophisticated sectors such as travel, insurance, logistics, and healthcare are still in their early days of adoption. There is a need for smart recommendation systems. Particularly in the travel sector, travel planning companies that started in the past two decades (e.g., Skiplagged in 2013, Google Flight in 2011, Airbnb in 2008, Kayak in 2005, HomeAway in 2004, SkyScanner in 2003, TripAdvisor in 2000, and Expedia in 1996) could have sustained their services with smart recommendation systems (Figure 1). Currently, travel decisions are predominantly made without the full knowledge of several alternatives and options based on user-specific preferences. Potential travellers resort to travel agents to recommend rather than make their own decisions due to a lack of information/awareness of new destinations. Furthermore, the information available over the Internet adapted with filtering and selection methods used by search engines can provide limited guidance only.

Figure. 1: Travel advice

With large amounts of information available online, travellers can get overwhelmed during their decision-making process. With recent developments in technologies and practical tools available to process big data, there exists an abundant opportunity to build automatic or semiautomatic systems that would provide a range of alternatives and suggestions based on user preferences to help travellers in their decision-making process. These form the key motivations of this research work that aims to design and develop a prototype of a travel recommendation system with edge technologies and effective models. However, prior to scoping an effective travel recommendation system, we considered the current state-of-the-art practices in the industry and their limitations. At present, most of the key travel industry players continue to rely on a destination-based recommendation approach in the form of travel packages. However, more inclusive data-driven insights are required for modern travel recommendation systems to provide personalized advice. A smart recommendation system could be developed to meet the varying needs of individual tourists in terms of personal tastes, interests, travel habits, and other contextual preferences influenced by time and monetary constraints. Currently, potential tourists are provided with a plethora of choices from a variety of fixed package-based recommendations that can lead to decision fatigue; furthermore, they fail to meet the consumer requirements effectively.

Recommender systems form a subclass of information filtering system to predict users' preferences and recommend items that are likely interesting to them. Companies using recommender systems focus on increasing sales because of very personalized offers and an enhanced customer experience. Recommendations typically speed up searches and make it easier for users to access the content they are interested in, and then surprise them with diverse offers they would have never searched for. Smart recommendations depend on intelligent modelling of the information filtering process, which is a key focus of this research work in developing a travel recommendation system that has a potential contribution to the growth of the tourism industry.

2. Literature Survey

Scharf et al. [1] proposed modeling uncertainty in recommendation data using probabilistic ranking instead of single-score methods. It introduces RankDist, an algorithm that computes the probability of an item's rank in a recommendation list to maximize user satisfaction. The study builds on prior work in probabilistic databases and demonstrates that rank-based methods, newly applied to recommender systems, offer both theoretical optimality and improved empirical performance.

Jewpanya et al. [2] proposed algorithm utilized an extended model of the Team Orienteering Problem with Time Windows (TOPTW) to account for mandatory locations and activities at each site. It offered trip planning that included a set of locations and activities designed to maximize the overall score accumulated from visiting these locations. To solve the proposed model, the Adaptive Neighborhood Simulated Annealing (ANSA) algorithm was applied. Tsai et al. [3] approaches accurately predict user preferences for individual POIs, they struggle to generate complete itineraries that accommodate personalized constraints, such as designated start/end locations and travel time limitations.

Halder et al. [4] proposed an adaptive Monte Carlo Tree Search (MCTS) algorithm for personalized POI selection and pruning, effectively handling multiple constraints in itinerary planning. Their approach integrates user preferences and temporal constraints to generate feasible and personalized travel itineraries. Guo et al. [5] Introduced the Top-Personalized-K Recommendation, a task focused on tailoring the number of recommended items to maximize individual user satisfaction. To achieve this, the authors propose PerK, a model-agnostic framework that selects the optimal list size by estimating and maximizing expected user utility using calibrated interaction probabilities.

Zhang et al. [6] proposed to enhance travel recommendations, Next-location recommendation techniques predict subsequent POIs based on users' prior trajectories, while top-k location recommendations present a selection of appealing POIs. Shrestha et al. [7] helped provide better suggestions to travelers, promoted decision-making, and raised satisfaction levels all around. The study emphasized the significance of questionnaire design, including demographic data, creating a strong association model using machine learning. Decision criteria were constructed based on the data quality being evaluated. Data from multiple sources were combined to create a comprehensive tourist database, and the recommender system included user feedback and decision-making guidelines.

Zheng et al. [8], looks for a particular destination or attraction, the aim was to predict the next location of the traveler, and a heuristic procedure based on a data mining approach was proposed. This procedure learns the mobility of the tourist against the past movements of visitors; i.e., it uses historical data. For this study, data was collected for travelers using GPS-like tracking applications at the Summer Palace in Beijing, China. The proposed model and study can contribute significantly toward providing better location-based services, promotions of tourist attractions, crowd control, etc. Personalized route predictions are systems that predict routes based on user requirements. A detailed review and survey of some approaches based on machine learning are presented by Sudhanva et al. [9]. In another study presented by Xu et al. [10], an improvised version of personalized route predictions and recommendation algorithms was proposed that uses the current congestion situation and user-preferred spots, and then builds a recommendation matrix.

Worndl et al. [11], based on a user's points of interest, propose a new method to design routes consisting of users' preferred spots; the user uses a website to enter his or her starting and end points in a tour. Then, the user is given recommendations of interesting places across that route. Here, the Dijkstra algorithm is used to find the shortest paths. In another study of a route recommendation system proposed by Sun et al. [12], a personalized system was proposed that works based on the user's preferences. This system is based on two-stage architecture where in the first stage, candidates are generated by using the support vector machine (SVM) model, and in the second stage, these candidates are ranked based on a gradient boosting regression tree that scores the candidates and updates the list with new ranks. Another personalized route recommendation system based on preferred spots is proposed in the studies presented by Cao et al. and Chen et al. [13]. The intelligent recommendation system proposed by Chen et al. in [14] is based on Hadoop in order to mend the scalability of the recommendation facility. A three-step algorithm for the recommendation of independent travel routes is proposed by Pan et al. [15]. In the first step, a 0–1 knapsack problem is modeled that under precise conditions selects landmarks in the destination. In the second step, through an analytic hierarchy process model, the selected landmarks are evaluated, scored, and selected through a simulated annealing algorithm. After that, the most rational and reasonable route is selected out of all the candidates. Finally, among all the landmarks, a route planning is generated as a traveling sales problem. An approach based on the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm that uses hot spots for route recommendation is proposed by Shen et al. [16] in this study, clusters of routes at the coarse level are generated based on distance. Recommendations are made based on a weighted tree that considers the time to drive, distance, velocity, and the attractiveness of the destination from an uncrowded to crowded hot spot for the optimal recommendations.

3. Proposed Methodology

The proposed system provides personalized travel recommendations for tourists in Indonesia by leveraging machine learning and hybrid models. Users can upload datasets, which are pre-processed using techniques such as handling missing values, encoding categorical variables, TF-IDF vectorization for textual reviews, and train-test splitting. Features are scaled or normalized when required, ensuring optimal model performance. For predictions, the system implements multiple models for comparative analysis LLR, SVC, RF, and the primary Neuro-Tree-Net model, which combines ET and ANN. The Neuro-Tree-Net captures complex nonlinear relationships in the data, improving prediction accuracy for both duration and recommendation score. The platform also integrates EDA capabilities, generating interactive visualizations such as histograms, scatter plots, boxplots, correlation heatmaps, and pair plots, helping users gain insights into tourism trends and patterns.

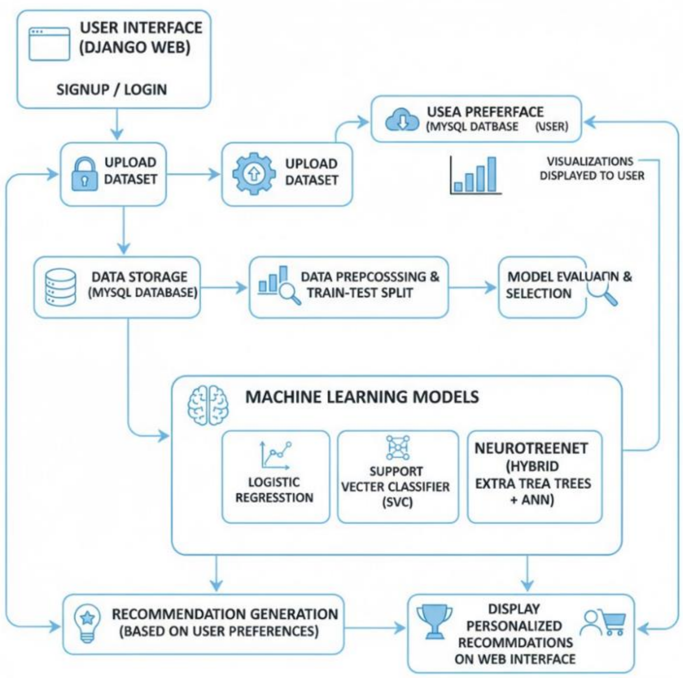

Figure. 2: Proposed system architecture.

Users can input constraints such as budget, travel duration, season, destination, and interests, and the system produces personalized predicted travel duration and recommendation scores as shown in Figure 2. Additionally, the system can generate AI-assisted travel suggestions using the XAI, providing tailored recommendations for each traveller.

3.1 Neuro TreeNet CART Model

The Neuro TreeNet Model is a hybrid machine learning architecture that combines the strengths of tree-based ensemble models (like ET or Random Forest) with Artificial Neural Networks (ANNs). By integrating these two approaches, the model can capture both hierarchical decision rules and complex nonlinear feature interactions, providing superior predictive performance compared to single-model approaches, as shown in figure 3. Tree-based models excel at handling categorical features, missing values, and capturing hierarchical relationships, while ANNs are powerful at learning high-dimensional nonlinear representations, such as patterns from TF-IDF vectors of reviews. The Neuro Tree Net model fuses these capabilities to leverage the best of both worlds.

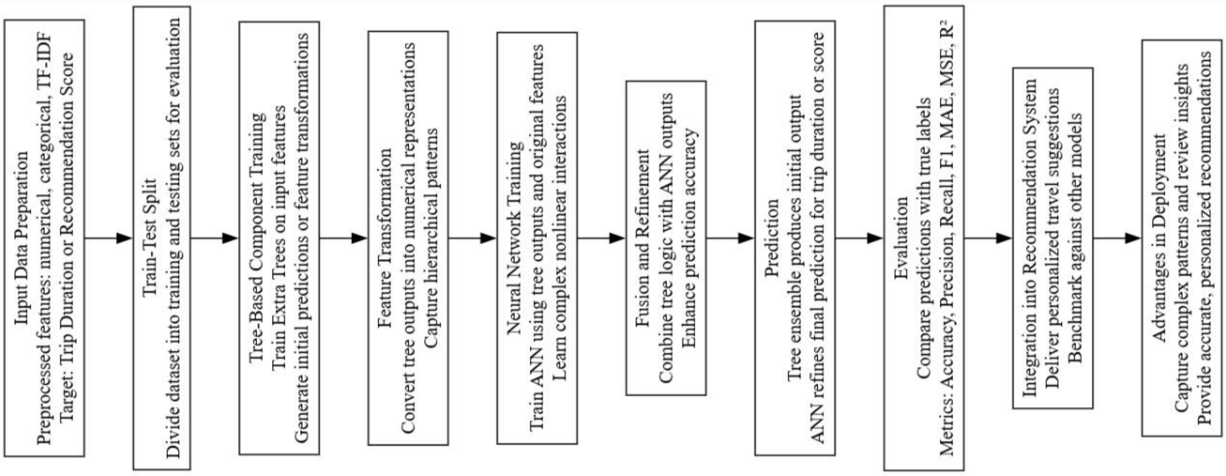

Figure. 3: Internal working of Neuro TreeNet model

Tree-Based Component Training (ET): A forest of ET is trained on the input features. Each tree identifies feature splits that best separate classes (or predict regression targets). The output of this step includes predicted values or transformed features for each training sample.

Feature Transformation: The outputs from the tree ensemble (predictions or leaf indices) are converted into numerical representations. These transformed features capture hierarchical relationships and patterns from the tree component that the neural network can further process.

Neural Network (NN) Training: The NN is trained using tree outputs combined with original input features. It learns complex nonlinear relationships and interactions that the tree-based component alone cannot capture, enhancing predictive performance.

Fusion and Refinement: The ANN refines the predictions from the tree component, combining hierarchical decision logic with nonlinear feature interactions. This fusion enables the model to handle high-dimensional, mixed-type features effectively.

Prediction: For a new user input, the tree ensemble first produces initial predictions, which are passed to the ANN. The final output is the predicted trip duration category (classification) or recommendation score (regression).

Evaluation: The model's predictions are compared with the true labels in the testing set. Performance metrics like accuracy, precision, recall, F1-score (for classification) and MAE, MSE, RMSE, R^2 (for regression) are computed to assess effectiveness.

Integration into the System: The Neuro TreeNet predictions are integrated into the recommendation system. Users receive personalized travel suggestions based on their preferences, and the model's outputs are combined with other models for performance benchmarking.

Advantages in Deployment: The hybrid structure allows the system to capture complex patterns in tourism data, leverage user reviews via TF-IDF, and deliver more accurate recommendations than single models like LLR, SVM, or RF.

4. Results description

This section presents the outcomes obtained from the implementation of the Travel AI system developed for tourism prediction and recommendation. The results demonstrate the performance of the ML models used for travel duration classification and recommendation score prediction. Various visualizations and evaluation metrics highlight the effectiveness of the implemented algorithms in analysing tourism data. The generated results illustrate the system's ability to process travel attributes, produce accurate predictions, and deliver intelligent travel recommendations through the integrated AI framework.

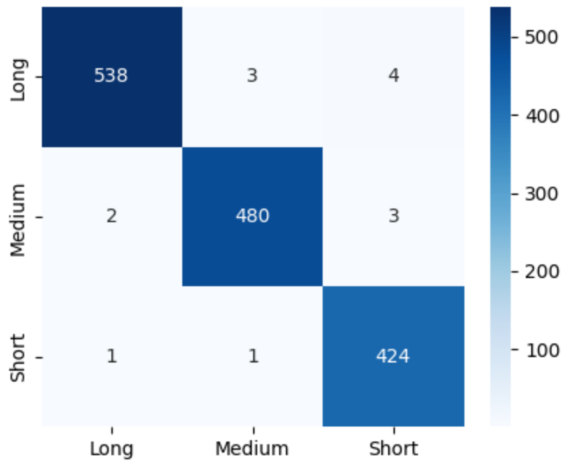

Figure. 4: Obtained confusion matrix of duration attribute from Neuro-Tree-Net

Figure 4 presents the confusion matrices obtained from Neuro-Tree-Net: The confusion matrix generated by the Neuro-Tree-Net CART model illustrates the classification output obtained from the hybrid tree-based learning approach implemented in the Travel AI system. The matrix shows a strong concentration of values along the diagonal, indicating a high number of correct predictions for travel duration categories. This result demonstrates the effectiveness of the Neuro-Tree-Net CART model in learning relationships between tourism features, textual review representations, and travel duration outcomes within the dataset.

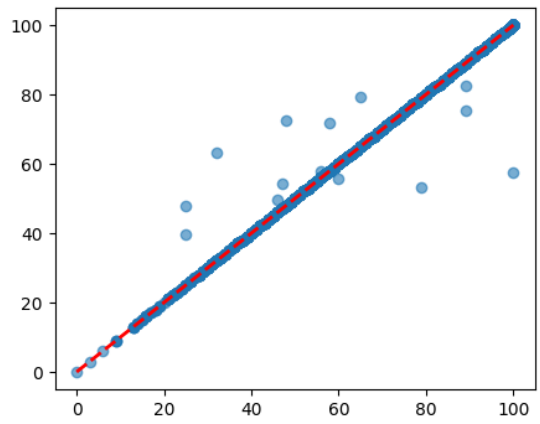

Figure. 5: Obtained scatter plot of recommendation score attribute from Neuro-Tree-Net.

Figure 5 presents scatter plots that illustrate the prediction performance of Neuro-Tree-Net: The scatter plot produced by the Neuro-Tree-Net CART model presents the predicted recommendation scores relative to the actual values in the dataset. The concentration of points near the diagonal reference line reflects strong agreement between predicted and actual scores. This distribution demonstrates the effectiveness of the Neuro-Tree-Net CART approach in modelling relationships between tourism features, review text representations, and recommendation score outcomes within the Travel AI recommendation system.

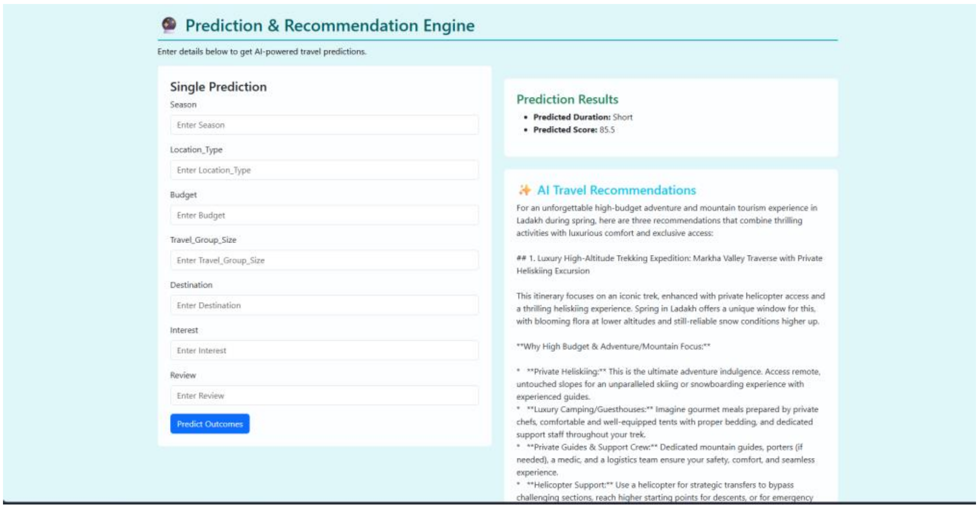

Figure. 6: Prediction on test data

Figure 6 presents the prediction output generated by the Travel AI system when test data is processed through the trained machine learning models. The prediction interface displays the estimated travel duration category and the recommendation score generated from the classification and regression models. The system processes input attributes such as destination, season, budget category, travel interest, and review information. These attributes undergo preprocessing operations including label encoding and TF-IDF transformation before entering the trained models. The Neuro-Tree-Net CART model produces the final predictions, which appear on the interface along with the recommendation score value. The system also generates intelligent travel suggestions through the integrated AI recommendation module, providing personalized tourism guidance based on the predicted results.

Table. 1: Classification performance comparison for travel duration prediction

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LR model	0.35	0.34	0.35	0.33
SVM model	0.36	0.35	0.36536	0.35
RF model	0.48	0.48	0.48	0.48
Neuro-Tree-Net	0.994	0.99	0.99	0.99

Table 1 presents the classification performance comparison of different machine learning models used for predicting the travel duration attribute in the Travel AI system. The evaluation metrics include Accuracy, Precision, Recall, F1-Score, and AUC. LR and SVM produce moderate classification performance with accuracy values around 0.35. The RF classifier shows improved performance with higher accuracy and balanced precision and recall values. The Neuro-Tree-Net CART model demonstrates the highest performance among all models with an accuracy of 0.99 along with very high precision, recall, and F1-score values. These results indicate that the Neuro-Tree-Net CART model provides highly accurate classification results for predicting travel duration based on tourism features.

Table 9.3: regression performance comparison for recommendation score prediction

Model	MAE (%)	MSE (%)	RMSE (%)	R^2 Score (%)
LR model	19.98	552.81	23.51	0.01
SVM model	19.94	553.88	23.53	0.008
RF model	18.46	494.67	22.24	0.11
Neuro-Tree-Net	0.155	3.77	1.94	0.99

Table 2 presents the regression performance comparison of different models used for predicting the recommendation score in the Travel AI system. The evaluation metrics include MAE, MSE, RMSE, and R^2 Score. LR and SVM Regressor produce higher error values and very low R^2 scores, indicating weaker prediction performance. RF Regressor shows better results with reduced error values and an improved R^2 score. The Neuro-Tree-Net CART model achieves the best regression performance with extremely low MAE, MSE, and RMSE values along with an R^2 score of 0.99. These results demonstrate that the Neuro-Tree-Net CART model produces highly accurate recommendation score predictions within the Travel AI system.

5. Conclusion

The Travel AI system presents an intelligent tourism recommendation platform that integrates machine learning techniques with a web-based interface for predicting travel duration and recommendation scores. The system processes tourism-related attributes such as destination, season, budget, travel interests, and textual reviews to generate accurate predictions and personalized travel suggestions. Data preprocessing techniques including label encoding and TF-IDF vectorization transform categorical and textual information into numerical representations suitable for machine learning models. Several classification and regression algorithms were implemented and evaluated to determine the most effective model for tourism prediction tasks. The classification models predict travel duration, while the regression models estimate recommendation scores for destinations. Performance evaluation using metrics such as accuracy, precision, recall, F1-score, MAE, MSE, RMSE, and R^2 score demonstrates that the Neuro-Tree-Net CART model achieves the highest predictive performance compared with other models. The system also integrates an AI-based recommendation module that generates travel suggestions based on user preferences and predicted results. The developed system provides a comprehensive platform for tourism data analysis, predictive modelling, and intelligent travel recommendation. The integration of data visualization, machine learning models, and AI-generated suggestions creates a decision-support tool that improves travel planning and enhances the tourism experience.

References

[1] Scharf, C.; Domshlak, C.; Gal, A.; Roitman, H. A Rank-Based Approach to Recommender. System's Top-K Queries with Uncertain Scores. Proc. ACM Manag. Data 2025, 3, 5.

[2] Jewpanya, P.; Nuangpirom, P.; Pitjamit, S.; Nakkiew, W. Optimized Travel Itineraries: Combining Mandatory Visits and Personalized Activities. Algorithms 2025, 18, 110. https://doi.org/10.3390/a18020110

[3] Tsai, C.Y.; Chuang, K.W.; Jen, H.Y.; Huang, H. A Tour Recommendation System Considering Implicit and Dynamic Information. Appl. Sci. 2024, 14, 9271.

[4] Halder, S.; Lim, K.H.; Chan, J.; Zhang, X. A survey on personalized itinerary recommendation: From optimisation to deep learning. Appl. Soft Comput. 2024, 152, 111200.

[5] Yu, J.; Guo, L.; Zhang, J.; Wang, G. A survey on graph neural network-based next POI recommendation for smart cities. J. Reliab. Intell. Environ. 2024, 10, 299–318.

[6] Zuo, J.; Zhang, Y. Collaborative trajectory representation for enhanced next POI recommendation. Expert Syst. Appl. 2024, 256, 1248.

[7] Shrestha, D.; Wenan, T.; Shrestha, D.; Rajkarnikar, N.; Jeong, S.-R. Personalized Tourist Recommender System: A Data-Driven and Machine-Learning Approach. Computation 2024, 12, 59. https://doi.org/10.3390/computation12030059.

[8] Zheng, W.; Huang, W.; Li, Y. Understanding the tourist mobility using GPS: Where is the next place? Tour. Manag. 2017, 59, 267–280.

[9] Sudhanva, G.M.; Kishore, S.; Dixit, S. Personalized dynamic route prediction using machine learning: A review. In Proceedings of the 2017 International Conference of Electronics, Communication and Aerospace Technology, Coimbatore, India, 20–22 April 2017. Volume 1.

[10] Xu, Y.; Tao, H.; Ying, L. A travel route recommendation algorithm with personal preference. In Proceedings of the 2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery, Changsha, China, 13–15 April 2016.

[11] Wolfgang, W.; Hefele, A.; Herzog, D. Recommending a sequence of interesting places for tourist trips. Inf. Technol. Tour. 2017, 17, 31–54.

[12] Sun, X.; Huang, Z.; Peng, X.; Chen, Y.; Liu, Y. Building a model-based personalised recommendation approach for tourist attractions from geotagged social media data. Int. J. Digit. Earth 2018, 661–687.

[13] Cao, L.; Tao, J.; Chen, B. Implementation of Personalized Scenic Spots Route Recommendation System. In Proceedings of the 2018 13th International Conference on Computer Science & Education, Colombo, Sri Lanka, 8–11 August 2018.

[14] Chen, X.; Zhou, L. Design, and implementation of an intelligent system for tourist routes recommendation based on Hadoop. In Proceedings of the 2015 6th IEEE International

Conference on Software Engineering and Service Science, Beijing, China, 18–20 October 2015.

[15] Pan, Q.; Wang, X. Independent travel recommendation algorithm based on analytical hierarchy process and simulated annealing for professional tourist. Appl. Intell. 2018, 48, 1565–1581.

[16] Shen, Y.; Ligang, Z.; Jing, F. Analysis and visualization for hot spot-based route recommendation using short-dated taxi GPS traces. Information 2015, 6, 134–151.