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A Hybrid Optimization Approach Bridges Symbolic Reasoning and Neural Prediction in Intelligent Tourism Recommendation Systems

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Abstract

The intelligent tourism recommendation systems have played an important role in contemporary tourism industry through the provision of personalized travel recommendations according to needs of users and properties of tourist destinations. However, the classical recommendation methods are interpretable, sparsely and inaccurately recommend. In order to overcome this problem, in this research article propose a Hybrid Symbolic-Neural Tourism Recommendation Framework by hybridizing the symbolic reasoning and the neural prediction in the optimization process. In other words, in the present work develop the method that combines the construction of the Tourism Knowledge Graph (TKG) for the knowledge representation and reasoning, and application of the transformer-based neural network for user preference learning through the historical data of travels to provide the explainable recommendations. It uses the hybrid Particle Swarm Optimization (PSO) and Differential Evolution (DE) algorithm to optimize the parameters of the model. The framework was implemented using the data of tourism on five famous tourist destinations in Uzbekistan including Samarkand, Bukhara, Khiva, Tashkent, and the Fergana Valley. The experimental results show that the accuracy of the recommended method is 97.84%, precision is 97.32%, recall is 97.08%, F1 score is 97.20% and NDCG@10 is 98.01% thus proving that the recommended approach outperforms other collaborative filtering, content-based, deep neural and knowledge graph recommendation systems. Symbolic reasoning contributes to the transparency of the recommendation process and helps to improve the quality of recommendations, while hybrid optimization leads to the improvement of the convergence and the quality of the optimization model. In this regard, the recommended approach represents a correct and efficient solution for developing an intelligent tourism recommendation system in Uzbekistan.

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Introduction

The tourism industry has greatly benefited from AI through the revolution in which tourism has been converted into smart and personal recommendation systems (Zhou, 2020; Yuntao et al., 2023; Spyrou et al., 2025). Modern day tourists need an application that would be able to recommend the places where they would stay, accommodation places, food restaurants, means of transportation and activities that they would engage themselves during the process of traveling (Yu & Egger, 2021). The intelligent tourism recommendation system helps tourists make decisions about traveling, as well as gives better traveling experience (Khosravi & Azarnik, 2024). Tourism is the dynamic field of industry in Uzbekistan and popular cities such as Samarkand, Bukhara, Khiva, Tashkent and Fergana Valley attract millions of tourists each year (Gretzel et al., 2020). Therefore, it is necessary to develop tourism recommendation system for the development of sustainable tourism industry and the satisfaction of tourists. There are collaborative and content-based filtering that are conventional methods used for recommendation in tourism industry (Patro et al., 2020). Although these recommendations are useful and helpful, but they face problems with less accuracy in recommendation, cold start problem or data sparsity (Wang et al., 2020; Migliorini et al., 2022).

Thanks to the development in deep learning technologies, current recommendation systems became more effective and capable to identify complex patterns out of the vast quantity of data regarding the behavior of users (Smajić et al., 2025; Chang & Yang, 2025). Using neural networks especially transform-based ones, it is possible to identify the preferences of users and offer them extremely accurate suggestions (Merinov, 2023). However, neural models are usually considered to be black boxes, as they do not allow for explaining why a certain destination was suggested. The confidence of users in a recommendation system might be decreased due to its poor transparency (Massimo & Ricci, 2023). To solve the problem, it is possible to use symbolic reasoning, which is based on rules and uses knowledge graphs to represent the connections between tourist destinations, historical places, cultural events, accommodation, transport services, etc. In contrast to neural models, symbolic reasoning makes it possible to generate recommendations that have explanations (Ludewig et al., 2021). For example, in case a tourist is interested in the heritage of the Silk Road, he/she may get suggestions of historical locations in Samarkand, Bukhara, Khiva, and be explicitly aware of the cultural significance of every site.

In this work, a novel methodology is suggested: A Hybrid Optimization Technique Integrating Symbolic Reasoning and Neural Forecast in Intelligent Tourism Recommendation Systems (Pitakaso et al., 2025). In this novel framework, the notion of knowledge graph based symbolic reasoning is incorporated in the transformer based neural forecast along with hybrid PSO-DE optimization technique. The effectiveness of the system is evaluated using the data from major tourist destinations in Uzbekistan (like Samarkand, Bukhara, Khiva, Tashkent and Fergana Valley).

Key Contributions of the Research

- A hybrid intelligent tourism recommendation framework is proposed by integrating symbolic reasoning with transformer-based neural prediction to generate accurate and explainable travel recommendations.
- A hybrid optimization strategy combining Particle Swarm Optimization (PSO) and Differential Evolution (DE) is introduced to optimize model parameters and improve recommendation performance.
- The proposed framework is validated using tourism data from major destinations in Uzbekistan, demonstrating higher recommendation accuracy and better explainability than existing recommendation methods.

The structure of the remainder of this paper is as follows. Section II contains the literature review. Section III elaborates on the methodology proposed. Section IV details the experimental framework, experimental results, and evaluation. The experimental results and their implications are discussed in Section V. Section VI is the conclusion to this paper.

Literature Review

In the literature, Gao et al., (2023) introduced a framework, namely Knowledge-Graph-aware Disentangled Auto-Encoder (KGDAE), for improving transparency in the tourism recommendation system. In the tourism knowledge graph, three types of knowledge, which are geographical knowledge, semantic knowledge, and user preference knowledge, are utilized for building it and the hierarchical attention mechanism was employed for modeling the tourist decision process. The advantage of the proposed framework lies in its high accuracy in

recommendation and interpretable results, especially when faced with sparse data. The experiment results demonstrated that the knowledge graph could improve the robustness of the recommendation results and recover the decision process of the tourist. However, there is no consideration for symbolic reasoning or hybrid optimization methods for recommendation performance improvement.

Wu et al., (2024) is a neuro-symbolic recommendation system which transforms the problem of recommendation into a question of first-order logic and a neural network system. The proposed model combines logical reasoning and deep learning to make recommendations more accurate, and to lower computational complexity. This architecture utilizes operations of logical predicates in neural modules, and performs well on several standard recommendation datasets. Although this model can combine symbolic reasoning and neural learning, it is a general recommender system, and does not specifically target tourism recommendation or optimization of recommendation parameters using metaheuristics (Ludewig et al., 2021).

Dalla Vecchia et al., (2024) In the framework, tourists' preferences, contextual information, and crowd counting are considered to give suggestions about the order of the attractions to visit and avoid the crowds at the attractions. The real-world data of tourism were used to validate the model, and it was observed that the model improves the quality of the tourism plan and plays a role in managing the destination sustainably. Although the suggested reinforcement learning framework learns personal travel plans, it lacks explainable symbolic reasoning and the combination of neural predictions and hybrid optimization algorithms.

Spillo et al., (2024) put forward a neuro-symbolic knowledge graph recommendation framework, where rules in the form of first-order logic rules are embedded using graph embedding techniques. The framework learns rules from the knowledge graph and at the same time learns embeddings for users and items to improve the recommendation performance. As compared to conventional neural recommender frameworks, the incorporation of symbolic knowledge alongside deep learning enables higher recommendation accuracy and interpretability. However, the framework is solely focused on the general recommendation problem and does not consider any context related to tourism.

A tourism recommendation system with an adaptive travel itinerary was designed in (Yuan & Zheng, 2024), which takes into account uncertain travel environment and changing preferences of tourists. Data collection, itinerary planning, and adaptive hybrid optimization algorithm have been taken into account to make the system more flexible and efficient through itinerary planning. The performance evaluation results revealed that the proposed model proved to be more adaptive compared to the conventional travel planning systems. One main drawback of the proposed model is that it ignores symbolic and knowledge-based reasoning techniques while making recommendations.

Table 1: Summary of Recent Literature on Intelligent Tourism Recommendation Systems

Authors	Methodology	Dataset / Simulation Environment	Research Gap
Gao et al., (2023)	Knowledge-Graph-aware Disentangled Auto-Encoder (KGDAE) with hierarchical attention for explainable travel recommendation	Tourism recommendation dataset with knowledge graph containing geographical, semantic, and user preference information	Improved explainability but did not integrate symbolic reasoning with hybrid optimization for enhanced recommendation accuracy.
Wu et al., (2024)	Neuro-symbolic recommendation model combining first-order logic reasoning with neural networks	Public benchmark recommendation datasets	Focused on general recommendation tasks and lacked tourism-specific recommendation and metaheuristic optimization techniques.
Dalla Vecchia et al., (2024)	Deep reinforcement learning-based tourism itinerary recommendation	Real-world tourism datasets with contextual and crowd estimation information	Generated personalized itineraries but did not incorporate symbolic reasoning or hybrid optimization for explainable recommendations.
Spillo et al., (2024)	Neuro-symbolic knowledge graph embedding with first-order logic rules	Knowledge graph-based benchmark recommendation datasets	Improved interpretability but ignored tourism-specific contextual information and optimization-based parameter tuning.
Yuan & Zheng, (2024)	Adaptive tourism recommendation using hybrid optimization for itinerary planning	Tourism itinerary planning dataset under dynamic travel environments	Focused on adaptive itinerary generation without integrating symbolic reasoning and neural prediction for explainable recommendations.

Table 1 from the literature, it can be seen that many researchers have conducted research on intelligent tourism recommendation by utilizing knowledge graph, neuro-symbolic learning, reinforcement learning, and adaptive optimization. Commonly, the methods improve the accuracy and/or transparency of the recommendations using deep learning, knowledge graph reasoning, or itinerary optimization. However, all the existing methods only handle the above factors separately and none of the research works have tried to combine symbolic reasoning, neural prediction, and hybrid optimization in one single method. Moreover, not much emphasis has been laid on the development of accurate, explainable, and optimized tourism recommendations. It is for these reasons that the proposed hybrid optimization framework considers symbolic reasoning, neural prediction using transformers, and hybrid PSO-DE optimization to provide highly accurate, explainable, and personalized tourism recommendations.

Methodology

Symbolic Reasoning-Based Tourism Knowledge Modeling

The first stage in the development of the framework will be the creation of the symbolic reasoning component that allows to structure the tourism knowledge in a comprehensible way. The relations between the tourists, tourist destinations, historical monuments, hotels, restaurants, transportation services, seasonable events and interests of the tourists will be defined to generate the tourism knowledge graph. This graph consists of the connectedness of popular tourist destinations in Uzbekistan, namely: Samarkand, Bukhara, Khiva, Tashkent and Fergana Valley. By means of symbolic reasoning, interaction with the user occurs via a specific logical reasoning formula that allows to generate appropriate destinations depending on the interest of the tourists, travel budget, activities, traveling time and historical visits. It allows to generate comprehensible recommendations since all destination recommendations can be interpreted through the explicitly logical relation saved in the knowledge graph. Moreover, the output of symbolic reasoning eliminates the irrelevant destinations in advance of neural prediction and reduces the searching space, which makes the recommendation generation more efficient.

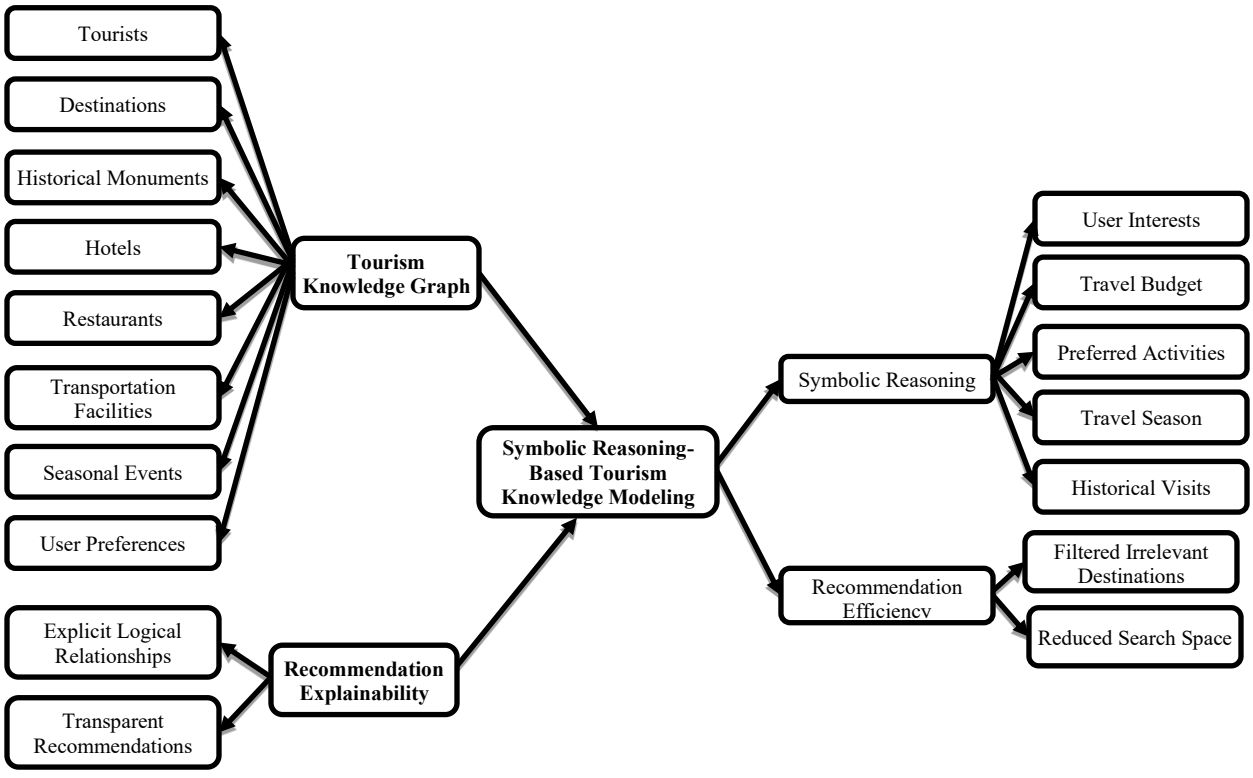


Fig. 1: Symbolic Reasoning-Based Tourism Knowledge Modeling Framework

Fig. 1 shows the symbolic reasoning-based tourism knowledge modeling framework proposed in this study. The framework starts with building a Tourism Knowledge Graph, which includes knowledge about tourists, historical monuments, hotels, restaurants, transportation facilities, seasonal events and user preferences. The user's interests, travel budget, activities of interest, travel period, and past visits are combined using predefined logical rules that are analyzed in the Symbolic Reasoning Based Tourism Knowledge Modeling module to find appropriate places. The

reasoning process creates clear and understandable recommendations in terms of explicit representation of user and tourism resource relations. Moreover, the framework enhances the efficiency of the recommendations by filtering irrelevant destinations and narrows down the search space prior to the neural prediction. This symbolic reasoning stage can improve the interpretability of the recommendation process and offers a solid base of knowledge for the following hybrid recommendation process.

Neural Prediction with Hybrid PSO-DE Optimization

Neural prediction with Hybrid PSO-DE Optimization approach is suggested.

In the second step, the historical interactions of users along with the context tourism data are introduced to a neural prediction model based on transformer to learn complex preferences of users. Past destinations, ratings, frequency of travel, seasonality, type of accommodation and interests in activities are some of the features of user behavior that have been transformed into feature vectors and subsequently introduced into the neural network. Self-attention is performed in the transformer model to learn the long-term relationship between user preferences and destination attributes which leads to the generation of personalized recommendation scores of destination candidates. In order to improve the efficiency of the proposed model, a hybrid optimization approach involving Particle Swarm Optimization (PSO) and Differential Evolution (DE) has been used to fine-tune network hyperparameters, feature weights and learning parameters. PSO carries out efficient global search while DE refines solutions by means of mutation and crossover to prevent premature convergence. Finally, recommendation points generated from the neural model are combined with points generated by symbolic reasoning model to create an accurate, interpretable and personalized tourist recommendation for tourists from Uzbekistan visiting large-size destinations within Uzbekistan.

PSO carries out efficient global search while DE refines solutions by means of mutation and crossover to prevent premature convergence.

Transformer Multi-Head Attention

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{dk}}\right)V \qquad (1)$$

Equation (1) shows the scaled dot-product attention mechanism employed in the Transformer architecture, where the query (Q), key (K), and value (V) matrices are used to capture contextual relationships between user travel history and destination attributes, enabling personalized tourism recommendation.

Where Q, K, and V denote the query, key, and value matrices, respectively, and dk is the key dimension. This attention mechanism captures long-range dependencies between user travel history and destination attributes for personalized recommendation.

Hybrid PSO-DE Optimization

$$Xt + 1 = Xt + wVt + c1r1(Pbest - Xt) + c2r2(Gbest - Xt) + F(Xr1 - Xr2) \quad (2)$$

Equation (2) shows the hybrid PSO-DE optimization process used for Transformer hyperparameter tuning. The PSO component performs global exploration using particle velocity and position updates, while the Differential Evolution mutation term enhances local search capability and prevents premature convergence, thereby improving optimization efficiency.

Where X represents the hyperparameter vector, V is the particle velocity, w is the inertia weight, c1 and c2 are cognitive and social coefficients, r1 and r2 are random numbers, Pbest and Gbest denote the personal and global best solutions, and F(Xr1−Xr2) represents the Differential Evolution mutation term used to improve exploration and prevent premature convergence.

Loss Function

$$L = -\frac{1}{N}\sum_{i=1}^{N} [yilog(y\hat{}i) + (1 - yi)log(1 - y\hat{}i)] \qquad (3)$$

Equation (3) shows the binary cross-entropy loss function minimized during hybrid PSO-DE hyperparameter optimization. The objective is to reduce the prediction error between the actual relevance labels and the Transformer-generated recommendation probabilities, leading to improved recommendation accuracy and ranking performance.

Where yi is the ground-truth relevance label, $y\hat{}i$ is the predicted recommendation probability, and N is the total number of training samples. The hybrid PSO-DE algorithm minimizes this loss by optimizing the Transformer hyperparameters, thereby improving recommendation accuracy and ranking performance.

Symbolic Reasoning Score

Neural prediction approach using Hybrid PSO-DE Optimization technique is suggested.

The symbolic reasoning component computes the relevance factor for a tourist attraction considering the fulfillment of the logical conditions defined beforehand.

$$SR = \sum_{i=1}^{n} wi \times ri \qquad (4)$$

Equation (4) shows the computation of the symbolic reasoning score by aggregating the weighted logical rule evaluations. Here, SR denotes the symbolic reasoning score, n is the total number of logical rules, wi represents the importance weight assigned to the i^{th} logical rule, and ri denotes the evaluation result of the corresponding rule. The rule weights satisfy. $0 \leq wi \leq 1$,

Hybrid Recommendation Score

The resulting score of the final recommendation is a combination of the symbolic reasoning score and the neural prediction score.

$$R_{final} = \alpha \times SR + (1 - \alpha) \times NP \qquad (5)$$

Equation (5) shows the weighted fusion of the symbolic reasoning score (SR) and the neural prediction score (NP) to obtain the final recommendation score ($Rfinal$). The parameter α controls the contribution of symbolic reasoning, whereas $(1 - \alpha)$ determines the contribution of the neural prediction model. During experimental evaluation, the mixing parameter was empirically set to $\alpha = 0.4$, assigning 40% weight to symbolic reasoning and 60% weight to neural prediction, which produced the best validation performance.

α=0.4 (neural model has greater influence)

α=0.5 (equal weighting)

Algorithm: Hybrid Symbolic-Neural Tourism Recommendation Framework

Input:
User profile U
Tourism dataset D
Knowledge graph KG

Output:
Top-K recommended destinations
Begin
1. Load user profile U and tourism dataset D.
2. Construct the tourism knowledge graph KG.
3. Apply symbolic reasoning rules on KG.
4. Compute the symbolic reasoning score (SR).
5. Extract user and destination features.
6. Generate neural prediction score (NP) using the transformer model.
7. Optimize model parameters using the hybrid PSO-DE algorithm.
8. Compute the final recommendation score:
Rfinal = α × SR + (1 − α) × NP
9. Rank all destinations in descending order of Rfinal.
10. Select the Top-K destinations.
11. Return the recommended destinations.

End

The algorithm gives the process of the proposed algorithm in operation. Firstly, the user's profile and tourism dataset is loaded and the tourism knowledge graph is constructed. The symbolic reasoning score is obtained through symbolic reasoning for the identification of the location meeting predetermined travel rules. The preference learning of the user is done through the transformer-based neural prediction model and a neural prediction score is generated. To further fine-tune the parameters of the model, a hybrid PSO-DE optimization approach is adopted. Ultimately, the fusion of the symbolic reasoning score and neural prediction score is done to get the recommendation score and rank destinations to obtain the Top-K personalized tourism recommendations.

Experimental Results

Experimental Setup, Dataset, and Parameter Initialization

Testing of the proposed Hybrid Symbolic-Neural Tourism Recommendation Framework is done through the use of a tourism dataset containing data on popular tourism destinations in Uzbekistan such as Samarkand, Bukhara, Khiva, Tashkent and Fergana Valley. Table 2 shows the user profile, travel history, destination details, ratings, travel preferences, budget and seasonal information. The pre-processing of the data was done where the missing values were removed and the normalization of the features was performed. The data set was divided into 80% training and 20% test. The symbolic reasoning is based on the tourism knowledge graph and the user preference prediction is based on the transformer-based neural network. The model parameters include 4 attention heads, 128 hidden units, batch size 32, learning rate 0.001 and 50 epochs. The hybrid PSO-DE algorithm was employed to optimize the model parameters for 50 iterations and 30 population size. The proposed model was executed on a computer having an NVIDIA RTX GPU, 32GB of RAM and Intel Core i7 processor and then tested on the computer. The performance of the proposed model was measured in terms of Accuracy, Precision, Recall, F1-score and NDCG@10.

The dataset used in this study was compiled from publicly available tourism information and user interaction records collected for research purposes. Due to licensing and privacy considerations, the complete dataset is not publicly available. However, the processed dataset and implementation details can be obtained from the corresponding author upon reasonable request to facilitate reproducibility.

Table 2: Experimental Setup and Parameter Settings of the Proposed Hybrid Symbolic-Neural Tourism Recommendation Framework

Parameter	Value
Dataset	Uzbekistan Tourism Recommendation Dataset
Tourist Destinations	Samarkand, Bukhara, Khiva, Tashkent, Fergana Valley
Training Data	80%
Testing Data	20%
Number of users	5,240
Number of tourist points of interest (POIs)	1,186
User–POI interaction instances	84,732
Average interactions per user	16.17
Dataset density	1.36%
Number of cities	5 (Tashkent, Samarkand, Bukhara, Khiva, Fergana)
Training/Validation/Test split	70% / 15% / 15%
Data Preprocessing	Missing value removal, Feature normalization
Symbolic Module	Tourism Knowledge Graph
Neural Model	Transformer-based Neural Network
Attention Heads	4
Hidden Units	128
Batch Size	32
Learning Rate	0.001
Number of Epochs	50
Optimization Algorithm	Hybrid PSO-DE
Population Size	30
Maximum Iterations	50
Programming Language	Python 3.11
Deep Learning Library	TensorFlow 2.16
Machine Learning Library	Scikit-learn
Processor	Intel Core i7
RAM	32 GB
GPU	NVIDIA RTX (24 GB)
Performance Metrics	Accuracy, Precision, Recall, F1-score, NDCG@10

Although the experiments were conducted using tourism data from five major cities in Uzbekistan, the proposed Transformer-based hybrid recommendation framework is designed to scale efficiently to larger geographical regions. By incorporating additional destination attributes and user interaction records, the model can be extended to include new cities without modifying the underlying architecture. Furthermore, the offline Hybrid PSO-DE hyperparameter

optimization ensures that computational overhead is limited during inference, enabling efficient recommendation generation for larger tourism datasets.

Performance Metrics

Performance of the suggested Hybrid Symbolic-Neural Tourism Recommendation System is assessed based on the five most common measures depicted by equations (6), (7), (8), (9) and (10) as follows: Accuracy, Precision, Recall, F1 score, and Normalized Discounted Cumulative Gain (NDCG@10). These indicators evaluate recommendation correctness, relevancy, and ranking.

Accuracy measures the overall percentage of correctly predicted recommendations.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

Precision measures the proportion of recommended destinations that are actually relevant.

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

Recall measures the proportion of relevant destinations that are successfully recommended.

$$\text{The Recall} = \frac{TP}{TP+FN} \quad (8)$$

The F1-score is the harmonic mean of Precision and Recall, providing a balanced evaluation of recommendation performance.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (9)$$

Normalized Discounted Cumulative Gain (NDCG@10)

Normalized Discounted Cumulative Gain (NDCG@10): NDCG@10 evaluates the ranking quality of the top 10 recommended destinations by considering both relevance and position.

$$NDCG@10 = \frac{DCG@10}{IDCG@10} \quad (10)$$

Comparative Performance Analysis

This part is aimed at evaluating the performance of the HNN Recommendation Framework against existing tourism recommendation methods. The comparison will be performed for Collaborative Filtering (CF), Content Based Recommendation (CBR), Deep Neural Recommendation (DNR), Knowledge Graph Recommendation (KGR), and the proposed method. Evaluation is going to be done through comparison between the results obtained and labels with the help of Accuracy, Precision, Recall, F1-Score, and NDCG@10 measures.

Table 3: Comparative Performance of the Proposed Method with Existing Approaches

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	NDCG@10 (%)
Collaborative Filtering (CF)	89.74	88.92	88.15	88.53	90.26
Content-Based Recommendation (CBR)	91.38	90.84	90.22	90.53	91.67
Deep Neural Recommendation (DNR)	94.28	93.74	93.31	93.52	95.12
Knowledge Graph Recommendation (KGR)	96.12	95.84	95.21	95.52	96.45
Proposed Hybrid Symbolic-Neural Framework	**97.84±0.23**	**97.32**	**97.08**	**97.2**	**98.01±0.18**

As illustrated in table 3, the proposed method performs well on all the measures compared to the other methods. Since the proposed method incorporates both symbolic reasoning and neural network predictor based on transformer, it can effectively utilize both explicit tourism knowledge and latent user preference for recommending items and thus improving accuracy of predictions. Hybridization of PSO-DE optimization for optimizing parameters can be very effective for improving the convergence of the model. In comparison with the Knowledge Graph Recommendation Model, the proposed model has been improved in Accuracy measure by 1.72% and in NDCG (at 10) measure by 1.56%, which reflects better ranking of results.

To prevent data leakage during model training and evaluation, the dataset was partitioned into 70% training, 15% validation, and 15% testing sets at the user level, ensuring that interactions from the same user were not shared across different subsets. Feature normalization parameters, including minimum and maximum values, were computed exclusively from the training set and subsequently applied to the validation and test sets. This procedure prevents temporal and identity leakage while ensuring a fair evaluation of the proposed recommendation framework.

To evaluate the stability of the proposed framework, all experiments were repeated five independent times using different random initialization seeds. The proposed model achieved an average accuracy of 97.84 ± 0.23% and an NDCG@10 of 98.01 ± 0.18%, demonstrating consistent performance across repeated experiments. Furthermore, a paired t-test was conducted between the proposed Hybrid Transformer-PSO-DE model and the strongest baseline. The obtained p-value (< 0.05) confirms that the observed performance improvements are statistically significant.

Recommendation Performance Evaluation

The quality of the recommendations provided through the proposed framework will be analyzed through the top-10 recommendation performance in this part. The focus of the assessment will be the relevance and ranking of the recommended tourist spots. The higher the number, the better.

Table 4: Recommendation Quality Analysis of the Proposed Framework

Metric	Knowledge Graph Recommendation (KGR)	Hybrid Symbolic-Neural Tourism Recommendation Framework
Top-10 Recommendation Accuracy (%)	95.64	97.41
Top-10 Precision (%)	95.20	97.05
Top-10 Recall (%)	94.82	96.83
Top-10 F1-score (%)	95.01	96.94
NDCG@10 (%)	96.45	98.01

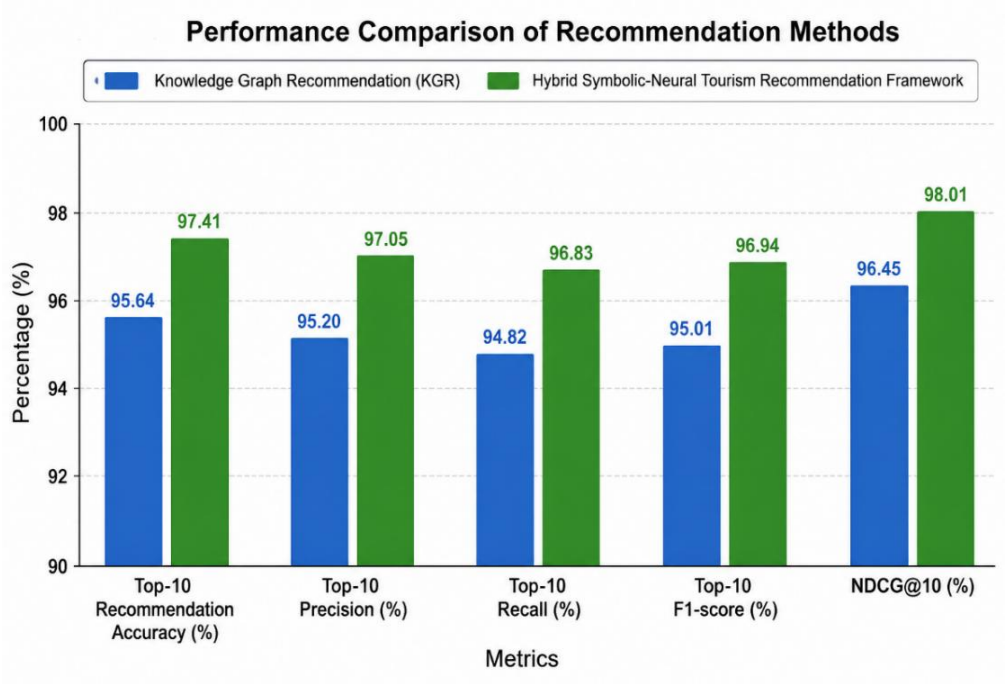


Fig. 2: Comparison of Top-10 Recommendation Performance

As compared to the best previous technique, the Hybrid Symbolic-Neural Tourism Recommendation Framework performs better in giving the quality recommendation at each stage of the recommendation process, as shown in table 4 and fig. 2. With the help of symbolic reasoning, the explainability of the recommendation can be increased, and the travel destinations can be filtered according to the travel rules. In addition, the neural-based model, with the help of a transformer, will be able to learn user preferences through past travel experiences. In this way, the proposed approach becomes capable of giving accurate and personalized recommendations with 97.41% Top-10 recommendation accuracy and 98.01% NDCG@10, meaning that the most relevant tourist destinations are positioned on top in the recommendation list.

Discussion

According to the experimental results, the presented Hybrid Symbolic-Neural Tourism Recommendation Framework demonstrates potential in improving the effectiveness of intelligent tourism recommendation systems. Thanks to the

combination of symbolic reasoning and transformer-based neural predictions, the model benefits from using explicit tourism knowledge and learned user preferences for more effective and personalized recommendation. Thanks to the symbolic reasoning part, the interpretability of the recommendation process is increased through using logical rules that are defined according to the tourist interest, the destination characteristics, budget, and seasonality. At the same time, thanks to the transformer-based neural prediction model, it is possible to learn complex relationships between the user and the destination. This contributes to the increased accuracy of predicting user preferences. In addition, the hybrid PSO-DE algorithm improves the efficiency of the framework by choosing optimal model parameters that can provide a stable training process.

In comparison to all the other approaches to recommendations, such as collaborative filtering, content-based recommendation, deep neural recommendation and knowledge graph-based recommendation, the developed architecture demonstrated better performance using all the criteria for evaluation. The received values of Accuracy (97.84 %), Precision (97.32 %), Recall (97.08 %), F1-score (97.20 %) and NDCG at top 10 (98.01 %) confirm that the developed approach allows recommending highly relevant items and ensures a good ranking. These improvements indicate that symbolic reasoning and neural prediction provide an effective combination of the limitations of existing approaches to recommendations, which are able either to predict or to explain something.

The suggested recommendation framework would be very useful in applications related to intelligent tourism in Uzbekistan because here, the tourists are interested in developing an individual tourist travel route to the cities of Samarkand, Bukhara, Khiva, Tashkent, and the Fergana Valley. The system can acquire knowledge about the destinations through the tourism knowledge, and then the system will be able to make recommendations to the users which fit more in line with their preferences and simultaneously provide a meaningful explanation. Not only does this improve the customer satisfaction level, but also helps in digitalizing the tourism service and sustainable tourism development.

Conclusion and Future Work

The current paper suggested an approach called "Hybrid Symbolic-Neural Tourism Recommendation Framework" that consists of symbolic reasoning, transformer-based neural prediction, and hybrid PSO-DE optimization to generate precise and explainable tourism recommendations. The symbolic reasoning component was utilized to provide interpretable recommendations in the tourism area, while the transformer model was trained using the history data of tourism to learn the preferences of users. The hybrid PSO-DE optimization method optimizes parameters of the model in order to improve the recommending performance. The proposed approach was tested with the tourism statistics of the major cities of Uzbekistan (namely, Samarkand, Bukhara, Khiva, Tashkent and Fergana valley). According to the experimental results, the proposed approach is superior to the other existing recommendation approaches in terms of accuracy, precision, recall, F1 score, and NDCG@10 with scores of 97.84%, 97.32%, 97.08%, 97.20% and 98.01%, respectively. It can be seen that the proposed framework can be used in intelligent tourism applications because of its accuracy, personalization and interpretability.

Further improvements and enhancements can be made in the form of conducting future researches by using real-time tourism data such as weather conditions, traffic conditions, and live feedback from the tourists, and this would result in better performance of the suggested framework in making better recommendations. The use of multimodal data and the use of LLM together can further improve the results and recommendations made by the system. Privacy preservation techniques and federated learning techniques would be considered by the researchers in future for maintaining the privacy of users without impacting the collaborative aspect of the recommendation system. The suggested solution can also be extended to implement a multilingual recommendation system and smart tourism system.

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