Digital Tourism Recommendation and Route Planning Model Design Based on RippleNet and Improved GA

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Tourism recommendation and route planning are important applications of smart tourism. To achieve digital tourism that integrates tourist attraction recommendation and route planning, this study first integrates RippleNet, an item representation enhancement module, and a knowledge graph to construct a new tourist attraction recommendation model. Secondly, to address the deficiencies of the genetic algorithm, it improves the population initialization and searching ability and designs the route planning model between tourist attractions. The experimental results indicated that the research-designed recommendation model had superior results in the evaluation of average accuracy mean and receiver operating characteristic curve, the average accuracy mean was higher than 0.9, and the curve area reached 0.924. At the same time, the model's root-mean-square error was as low as 0.316, the average absolute error was as low as 0.247, and the maximum of the R-squared index reached 0.844, and the Huber loss The lowest value was 0.215. The combined metrics verified the superiority of the model. The mean inverse ranking and comprehensive coverage verified the recommended utility of the model. In addition, the improved genetic algorithm's hypervolume index and anti-generation distance evaluation index indicated the rationality of the improved strategy, with clear path planning results and high scores of path fluency and rationality. This research can enhance the level of tourism service function, realize the personalized customized service of tourism travel, and enrich the tourists' experience to promote the development of digital tourism economy.

Povzetek: Študija združuje RippleNet in izboljšani genetski algoritem za izboljšanje digitalnih turističnih priporočil in načrtovanja poti, kar dosega boljšo natančnost, učinkovitost in zadovoljstvo uporabnikov.

1 Introduction

The improvement of national economic living standards has led to the continuous expansion of the global tourism industry, the number of tourist attractions and tourists are rising, and people's demand for tourism experience is also rising. The application of 'Internet + Tourism' technology has become a new direction for tourism transformation with the development of computer technology. Encouraging tour operators to develop digital tourism and applying modern information technology to promote high-quality tourism development has become the key to accelerating the construction of Smart Tourism (ST) scenic spots [1-2]. Information technology has revolutionized the tourism industry, providing new opportunities for growth and development. Cloud computing, artificial intelligence and big data analysis have facilitated the management and delivery of services. Additionally, technologies such as the virtual reality and augmented reality have enhanced the tourist experience [3]. With the increasing demand for tourism experience, personalized and customized tourism services have become a strong trend. However, in the face of the explosive growth of information on the Internet, "Information overload" leads to tourists not being able to effectively filter and compare tourist attractions, which increases the difficulty of planning travel routes [4-5]. How to provide authoritative and accurate information in the sparse data to meet users' needs and preferences has become an urgent challenge for digital tourism [6-7]. However, the sparsity of massive data causes the traditional User Collaborative Filtering (UserCF) to produce the problems of cold start and recommendation result accuracy degradation, and the recommendation limitations are strong [8]. Based on this, the study firstly selects Knowledge Graph (KG) recommendation technology, utilizes item representation enhancement module with RippleNet model to improve the semantic information of Genetic Algorithm (GA) on items, and constructs a tourist attraction Recommendation Modeling (RM) based on GA and deep learning. Then the travel routes between different attractions were planned using the improved GA to customize the travel personalized recommendation planning model. The study is broken up into four sections. The first section reviews the current status of domestic and international research on digital tourism attractions recommendation and Route Planning (RP). The second part proposes the RM that fuses deep learning with GA and the RP model for attractions based on improved GA. The performance and impact effects of the algorithms designed by the research are experimentally analyzed in the third part. The fourth part summarizes and generalizes the experimental results. This research is expected to improve the intelligence and personalization of tourism services and accelerate the digital transformation of tourism industry.

2 Research backgrounds

Enhancing visitor experience, improving visitor services, and making full use of computer technology to adapt to the tourism industry to provide personalized, interactive, and immersive tourism services are the core of creating ST. ST is a hot topic of wide attention all over the world, and many researchers and scholars have carried out rich research around digital tourism. The real road condition information at picturesque locations is frequently disregarded by traditional scenic RP. Wang et al. chose the A* algorithm, the most efficient direct search technique for determining the shortest path of a static road network, to tackle this issue. They then created an enhanced version of the A* algorithm that takes into account the entire cost of the road. The influence elements of road conditions were added to the A* algorithm's evaluation function, and the heuristic function was weighted by exponential decay. Simulation experiments verified the feasibility of the method, effectively reducing the path planning actual and path cost [9]. The unreasonable allocation of resources in scenic spots will lead to the decrease of tourists' satisfaction and the decrease of scenic spots' income. Li et al. established a mathematical model with the objective function of maximizing the total satisfaction of each tourist group, taking into account the age and preferences of the tourists, the carrying capacity of the tourist routes, and the thorough planning of the tourist routes. Additionally, utilizing the knowledge model, a hybrid Ant Colony Optimization (ACO) based on knowledge was created to enhance the algorithm's solution quality. The results of simulation experiments showed that the enhanced ACO has a greater path optimization effect and is more efficient at handling the tourism RP problem [10]. Traditional multi-objective evolutionary algorithms have the problems of uneven distribution of optimization solutions and weak diversity in solving tourism route optimization problems. Zheng et al. designed an evolutionary algorithm for multi-objective travel route recommendation based on decomposition of two-stage Pareto hierarchy. The method utilized the congestion mechanism between extreme and intermediate populations, the weights of the cross-mutation sub problem, and the Pareto stratification to ensure the distribution and diversity of the algorithm. The findings demonstrated that the method has a competitive advantage over other benchmark algorithms in terms of five test functions, hyper volume and inverse generation distance metrics, and recommended tourism routes with better distribution and diversity [11]. Existing tourism RP models mostly focus on attraction features or tourist behavioral features, or customize itineraries based on interactive interfaces, but these RP approaches lack route evaluation or destination image perception. Zhang et al. designed an interactive visual analysis system for tourism RP by communicating and discussing with industry experts, which introduced an automatic route optimization algorithm and multiple interactions to help users optimize and adjust their itineraries. Finally, the usability and effectiveness of the method were evaluated with the help of case studies and expert interviews [12].

Xu et al. used historical traveler data and data from the public road network to extract tourist preferences, point-of-interest relationships, and edge attraction values in order to better optimize the tourism RP technique. They then created a customized RP model based on urgency. The algorithm was able to generate customized itineraries for tourists, as demonstrated by the experimental findings, and the model enhanced GA based on gene replacement and gene splicing operators [13]. To make tourism more competitive, Thumrongvut et al. created a mixed integer linear programming model. They used a random variable neighborhood search and an improved differential evolution operator with k-variable shifts to find the model's best solution. With the help of this model to analyze the design of tourism routes and tourism RP, it can facilitate the management of tourism enterprises and ensure tourism revenue [14]. Tang et al. studied the issue of inbound visitor volume forecasting in order to assist the relevant departments in making more informed tourism plans and enhance the effectiveness of resource allocation. A hybrid forecasting model of inbound tourism demand was constructed by combining the fractional-order non-zero discrete gray model with the firefly algorithm. The dataset of incoming tourists from prior years confirmed the model's validity [15]. The tourism industry can utilize data analysis techniques to extract potentially useful information or knowledge, but existing data analysis methods have drawbacks such as overfitting, low accuracy, local minima, and sensitivity to noise. To address these issues, Sharma et al. designed a data mining strategy based on Support Vector Machines with Mare Optimization. The method also combined Extended Kalman Filter, Mantaray foraging algorithm to process the selection data. The higher performance of the model was confirmed by the experimental results [16]. Information overload creates difficulties in analyzing tourism-related data, leading to information confusion among tourists and managers. To assist scenic area managers in identifying strengths and weaknesses in the scenic area development process, and to aid tourists in finding scenic destinations that meet their needs, Luo et al. developed an enhanced tourist destination image mining and analysis model. This model combines the latent Dirichlet allocation theme extraction model, word frequency-inverse document frequency weighting, sentiment analysis, and probabilistic hesitant fuzzy algorithms. Jiuzhaigou, China, was analyzed as an example, and the model accurately identified the advantages and disadvantages in scenic area development, which is beneficial for tourists to choose attractions and scenic area improvement [17]. Attractions RM is very critical in solving the information overload problem, and most of the existing RMs are dedicated to improving RM accuracy, which leads to a lack of diversity in recommendation results. Lin et al. utilized “attraction features” to complete the design of diversity RM. The model was divided into two phases: theme diversity optimization model and minimizing misclassification cost optimization model, and the real tourism dataset verified the accuracy and diversity of the model [18].

In conclusion, Table 1 summarizes the current status of research on many technologies related to RP tourism. However, research on tourist advice and planning still falls short of the demands of travelers seeking customized and multipurpose travel experiences. Therefore, the study chooses GA recommendation technology and explores the semantic information expression of items and personalization enhancement in recommendation technology.

Table 1: Summary of the current state of research

Literature	Advantages	Disadvantage
Wang et al [9]	Low calculation time and road cost	Not considering obstacles and road conditions information, increased path length
Li et al [10]	Consider tourist satisfaction	Only considering unconstrained tourism resources
Zheng et al [11]	The update efficiency and population diversity of the solution are high; Tourism routes have better distribution and diversity	Large computational load and long training time
Zhang et al [12]	High interactivity	The planning results are rough, and the model has poor granularity
Xu et al [13]	The model explores the interests and preferences of users	The model has poor capture of time series
Thumrongvut et al [14]	Solved the solution flaw of differential evolution algorithm	The model is complex and requires a large amount of computation
Tang et al [15]	The advantages of integrating non-homogeneous discrete grey models with firefly algorithms	Complex model building
Sharma et al [16]	Integrating the advantages of multiple algorithms, low computational complexity, and ability to handle data noise	Not combined with practical tourism needs
Luo et al [17]	Multi technology integration	The model is complex and only considers the needs of tourism management
Lin et al [18]	Multi stage model with good recommendation performance	There is still room for improvement in recommendation accuracy and diversity

3 Travel recommendation and route planning model design based on RippleNet with Improved GA

The traditional standardized tourism routes can no longer meet the users' pursuit of personalized and unique tourism experience. Personalized recommendation of tourist attractions and customized travel routes can help to enhance the tourists' playing experience, improve customer satisfaction, and also enhance the competitiveness of the industry for tourism service providers [19-20]. The use of computer technology to drive the development of tourism digitalization is an important direction of change in the tourism service industry. The study is centered on tourist attraction recommendation and attraction travel RP.

3.1 Ontology-based knowledge graph construction for tourist attractions

The study builds RM of tourist attractions based on GA, KG is a graphical structure for organizing and representing knowledge, which consists of entities, relationships and attributes. As an important branch of knowledge engineering, the establishment and maintenance of KG requires extracting and integrating information from multiple data sources and constructing relationships between entities, which provides a powerful knowledge base for the development of artificial intelligence [21-22]. KGs are categorized into two types:

open domain and domain. Open domain KGs are GAs that cover a wide range of knowledge and span multiple domains, and contain different types of entities, relationships, attributes, and complex relationships between different domains, such as Google GA, Baidu GA, etc., which are mainly used in search engines, natural language processing, information retrieval, and other fields. Domain KG refers to domain-specific GA, which mainly focuses on domain-specific entities, relations and attributes, provides more in-depth in-domain knowledge, supports information query, reasoning and analysis in specialized domains, and helps users make scientific and accurate decisions [23].

The RM of the research design is constructed based on the domain KG. The domain KG consists of two key components: schema-layer learning and fact-layer learning. Schema layer learning is the backbone of the graph for determining the structure and framework of the GA, including defining schemas, constraints, and rules for entities, relationships, and attributes, which involves the mining and extraction of domain expertise and semantic rules. Fact layer learning utilizes ternary knowledge expressions to define relationships between entity information and populate the actual data content of the GA. Fact layer learning involves information extraction and mapping.

GA is constructed with data from various public tourism-related platforms and encyclopedic websites, etc. Writing a crawler is utilized to automatically obtain relevant information from websites or data sources. The main process of writing a crawler includes determining the crawling target and crawling content; analyzing the structure, URL format, and data presentation of the target website; and selecting a crawler tool to crawl the attraction information. The study utilizes a top-down approach to construct a knowledge graph (KG) by defining the attraction entity as the name, grade, address, opening time, visiting season, and price of the attraction. The schema layer then defines the ontology and completes the extraction of knowledge. The construction process of the attraction GA is illustrated in Figure 1.

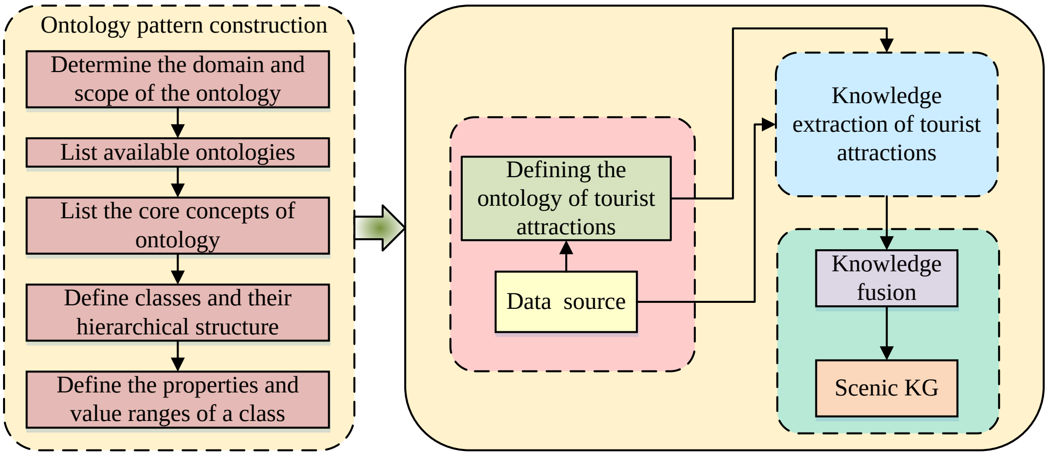


Figure 1: Construction process of scenic spot knowledge graph

The KG construction process uses entity alignment and disambiguation to process data from different data sources. Entity alignment links entities describing the same entity in different data sources for knowledge integration and querying across data sources. Entity alignment deals with the problem that a noun corresponds to multiple meanings, and for different attraction names, the research adopts entity alignment by judging entity strings, and the processing is shown in Figure 2. Entity disambiguation, on the other hand, identifies the specific entity involved in the denotation in the text and removes the ambiguity of the entity denotation. Finally, the GA constructed by the study is stored in the Neo4j database. Unlike traditional relational databases, Neo4j uses a graphical structure to store and process data. It utilizes nodes and relations to represent entities and their associative relationships, allowing for the expression of complex associations.

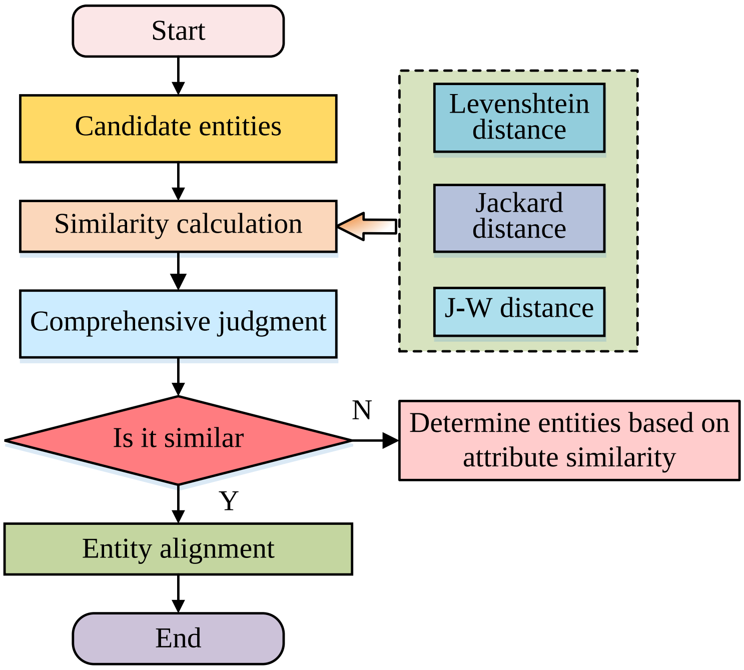


Figure 2: Entity alignment processing flow

3.2 Design of recommendation modeling for tourist attractions based on knowledge graph and RippleNet

GA belongs to a kind of semantic network, which performs knowledge reasoning based on existing knowledge and rules to achieve interpretability of attraction implicit information, which can provide more accurate and personalized search results for search engines. Nevertheless, when using GA to support attraction RM design, the relationship between users and implicit information of attractions is not taken into account. In order to increase the accuracy of RM, the study creates an item representation improvement module that establishes an implicit relationship between users and attractions. The set of users is defined as $U=\{u_1,u_2,...,u_m\}$, the set of attractions is defined as $V=\{v_1,v_2,...,v_n\}$, and the interaction matrix between users and attractions is denoted as $Y \in \mathbb{R}^{m\times n}$. the process of calculating the element y_{uv} of the interaction matrix is shown in Equation (1).

$$y_{uv}=\begin{cases}1 & interaction(u,v)\ is\ observed \\ 0 & otherwise\end{cases} \quad (1)$$

Define GA as $G=\{(h,r,t)h\in E,r\in R,t\in E\}$, with R and E denoting the set of GA relationships and entities, respectively. Predicting users' potential interest in attractions they haven't interacted with is the main responsibility of RM. The prediction function is defined as $y_{uv}=F\{u,v|\theta,Y,G\}$, with F denoting the function and θ denoting the prediction model parameters. The model framework comprises two parts: enhance item representation (Eir) and user interest module Ripple [24], as shown in Figure 3. Figure 3 shows that the user's historical interests are extracted using Transformer Layer and pooling methods. Then, the historical interests are combined with the attractions in the graph convolutional neural network to obtain item vectors containing interaction information. The item vectors are then processed with the user's interest module Ripple to obtain the user's interest vectors for the attractions, and the user's personal interest vectors are accumulated. Finally, the item vectors are concatenated with the user's personal interest vectors, and the prediction results are outputted through the fully connected layer.

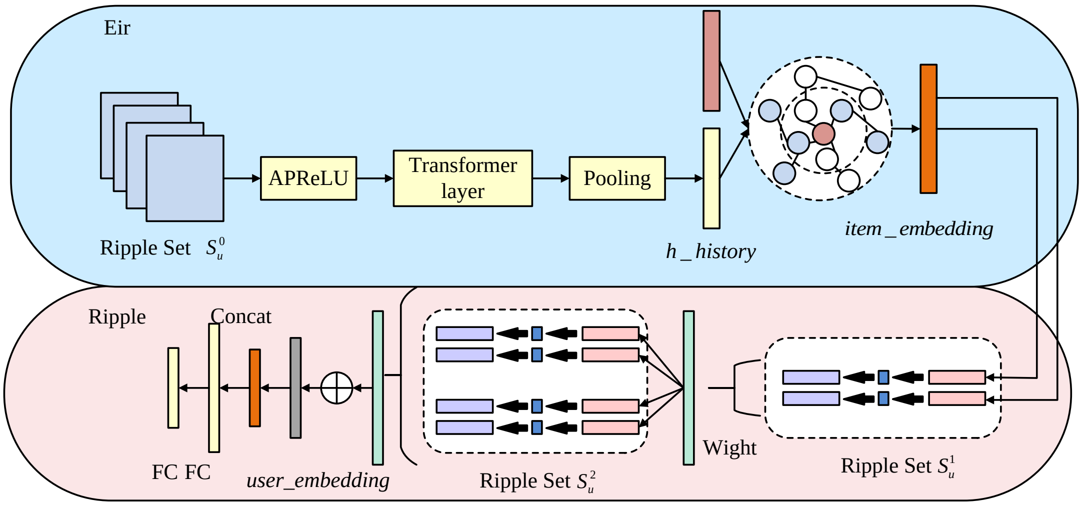


Figure 3: Eir ripple model framework

The information of the attractions crawled from the web platform is not enough to provide a complete representation of the attractions, and the study takes the user's historical interests S_u^0 and the attractions v as model inputs. S_u^0 is first extracted with the help of Asymmetrically Pre-trained Rectified Linear Unit (APReLU) to contain the feature information of user preferences. APReLU is developed based on Squeeze-and-Excitation module (SE) with ReLU activation function. Additionally, Figure 4 depicts the schematic organization of SE and APReLU.

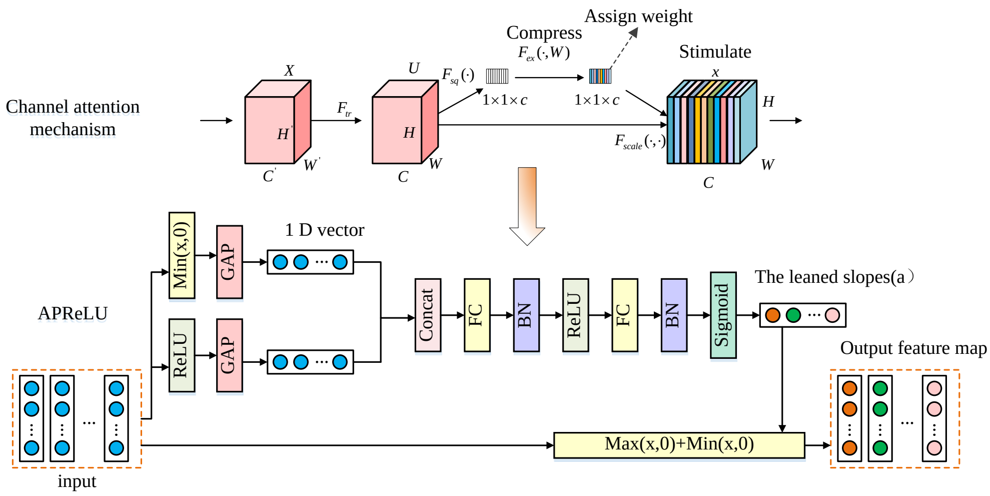


Figure 4: Structural schematic diagram of APReLU and SE

The computation process of the channel attention mechanism M_c is shown in Equation (2), where $MaxPool$ and $AvgPool$ denote maximum pooling and average pooling, respectively. MLP is multilayer perceptual machine and σ denotes activation function. F denotes image feature.

$$M_c(F)=\sigma\left(MLP\left(AvgPool(F)\right)+MLP\left(MaxPool(F)\right)\right)\quad(2)$$

The SE module implements channel attention through two steps, Squeeze and Excitation, Squeeze compresses the channel features through global average pooling, and Excitation learns the importance of the channel through a fully connected network to achieve the enhancement of important features. APReLU introduces asymmetric parameters based on the traditional ReLU activation function, which increases the flexibility of activation features and improves the performance and convergence speed of the network.

Equation (3) illustrates the calculating procedure that is used to extract the hidden information between the user's past interests and attractions using the Transformer layer. In Equation (3) Q,K,V denotes the query, key, and value terms in the attention mechanism, and W denotes the weight matrix. S denotes the splicing result of inputting the value of Q,K,V after projecting h times on W into multi-Head layer. b_1, b_2 denote constants. Finally, the pooling operation is used to get the historical interest of the user.

$$\begin{cases} head_i = Attention\left(S_u^0W^Q, S_u^0W^K, S_u^0W^V\right) \\ S = Multi\text{-}Head\left(S_u^0\right) \\ X = Add\ \&\ Norm\left(S_u^0 + S\right) \\ h\_history\_no\_pooling = \mathrm{Re}LU\left(W_2 \cdot \mathrm{Re}LU\left(W_1 \cdot X + b_1\right) + b_2\right) \end{cases} \quad (3)$$

The predicted attractions and historical interests are operated by graph convolution to learn the association between the two, and the calculation of preferences for different relations is shown in Equation (4). π_r^u denotes the user's preference for relation r and g denotes the function that calculates the degree of preference.

$$\pi_r^u = g(u,r) \quad (4)$$

The user relationship score normalization is calculated in Equation (5), and $N(v)$ denotes the set of entities in KG that are directly connected to attraction v.

$$\pi_{r_v,S_u^0}^{h\_histroy} = \frac{\exp\left(\pi_{r_v,S_u^0}^{h\_histroy}\right)}{\sum_{S_u^0 \in N(v)} \exp\left(\pi_{r_v,S_u^0}^{h\_histroy}\right)} \quad (5)$$

To decrease the computational pressure caused by too large $N(v)$, the study fixed some of the neighbor nodes and limited the depth of the neighborhood, and the processing is shown in Equation (6). In Equation (6), $S(v)$ is the set of neighbor nodes and e is the neighbor nodes. k denotes the number of fixed nodes.

$$S(v) = \{e \mid e \in N(v), |S(v)| = k\} \quad (6)$$

Finally, the attraction v is aggregated with the set $v_{S(v)}^{h\_history}$ of k nodes in the attraction domain, and the calculation process of attraction vector $item\_embedding$, which contains information about the interaction between the user and the attraction, is shown in Equation (7). In Equation (7), W^{EIR} and b^{EIR} denote the weights and bias terms of the fully connected layer, respectively.

$$item\_embedding = \sigma\left(W^{EIR}\left(v + v_{S(v)}^{h\_history}\right) + b^{EIR}\right) \quad (7)$$

S_u^0 is utilized as the seed of KG in the user interest module Ripple, which propagates up the chain to produce additional ripple sets S_u^{hop}. RippleNet represents the process of propagation of user interests on the KG, where the user's historical information spreads outward like drops of water. And the organization of Ripple Set is shown in Figure 5 [25-26].

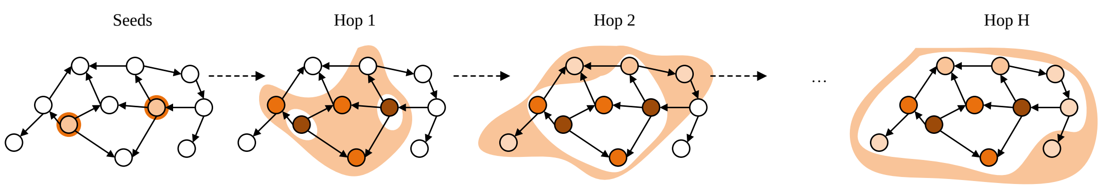


Figure 5: Ripple Set organizational structure

The Ripple calculation process is shown in Equation (8), where G is the KG of all attractions. ε_u^{hop} and S_u^{hop} are the set of entities and the set of neighbors that user hop jumps, respectively. h denotes the attractions connected to the user.

$$\begin{cases} \varepsilon_u^{hop} = \left\{t \mid (h,r,t) \in G, h \in \varepsilon_u^{hop-1}\right\}, hop = 1,2,\dots,H \\ S_u^{hop} = \left\{(h,r,t) \mid (h,r,t) \in G, h \in \varepsilon_u^{hop-1}\right\}, hop = 1,2,\dots,H \end{cases} \quad (8)$$

Ripple set first ripple diffusion S_u^1 process similarity P_i calculation is shown in Equation (9), P_i that is the similarity of the user and attraction embedding.

$$P_i = \frac{\exp\left(item\_embedding^T h_i r_i\right)}{\sum_{(h,r,t)\in S_u^1} \exp\left(item\_embedding^T h_i r_i\right)} \quad (9)$$

The calculation of the user's interest for the first hop is shown in Equation (10). Repeating the computation of this process then the user's interest representation vector user_embedding is obtained.

$$o_u^1 = \sum_{(h_i, r_i, t_i)\in S_u^1} P_i t_i \quad (10)$$

Finally, $item\_embedding$ is horizontally spliced with user_embedding using the concat method, and the computational procedure is shown in Equation (11). y_{uv} denotes the prediction result and FC denotes the fully connected layer [27].

$$\begin{cases} FC\_input = Connect\left(item\_embedding, user\_embedding\right) \\ y_{uv} = sigmoid\left(W_2 \cdot \mathrm{Re}\,LU\left(W_1 \cdot FC\_input + b_1\right) + b_2\right) \end{cases} \quad (11)$$

3.3 Design of route planning model for attraction traveling based on improved genetic algorithm

Using deep learning and GA, the study generates a user-recommended list of tourism destinations. From there, the travel routes between the attractions are further examined for planning purposes. When planning a route between tourist attractions, it is important to consider factors such as distance, travel time, mode of transportation, food and accommodation options, and personal preferences. This is a multi-objective optimization problem that requires the establishment of a mathematical model for path planning. The chosen path planning algorithm for this study is GA. GA is a kind of heuristic search algorithm simulating the genetic and evolutionary process in the natural world, and searches for the optimal solution or near-optimal solution through the simulation of Natural selection, crossover and mutation and other mechanisms to search for optimal solutions or near-optimal solutions, is widely used in optimization problems, the traditional GA workflow is shown in Figure 6 [28-29].

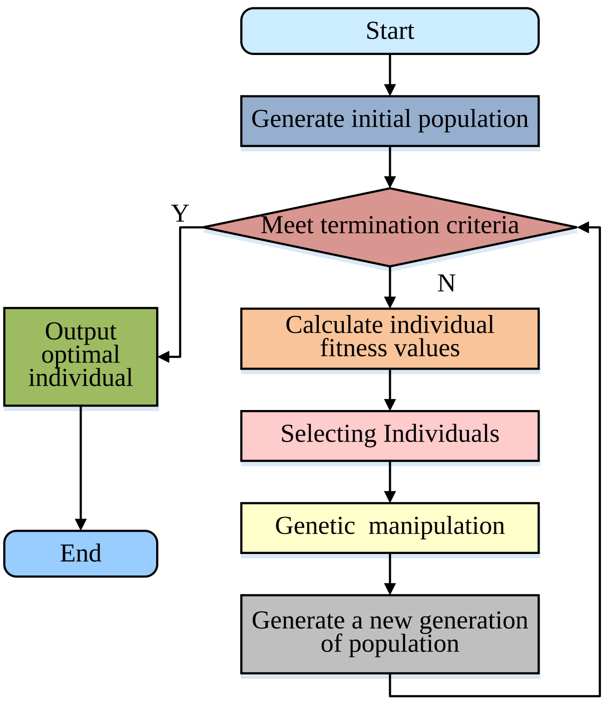


Figure 6: Traditional GA workflow diagram

GA encodes different travel routes binary as different chromosomes and treats the set of route solutions as an initialized population. A fitness function is designed to evaluate the superiority or inferiority of each individual in the population. Then, a set of initial solutions is generated, and the quality of the solutions is continuously optimized through genetic operations to obtain a better solution. The global optimal solution of the multi-objective optimization problem, or the person with the highest fitness value in the population, is found through non-stop iteration in the GA, which is designed to resemble the mechanism of superiority and inferiority in nature [30]. The study uses roulette selection method for individual selection, and the probability p_i of being selected is calculated in Equation (12). In this equation, f_i denotes the fitness value of the individual in the population.

$$p_i = \frac{f_i}{\sum_{i=1}^{n} f_i} \tag{12}$$

The selected superior individuals are used as parents for crossover operations to recombine the gene segments of the individuals to form new individuals. The study uses partial matching crossover to perform crossover operation, and then changes the values of certain genes on the chromosomes of individuals of the population with a small probability to increase the exploration ability of the search space. However, GA still has the defects of redundant iteration, over-reliance on the initial population, and imperfect convergence mechanism. The study introduced AC to improve GA. ACO is a heuristic search algorithm that mimics how ants release pheromones to find the best path while they look for food. It is developed as a result of observing how ants search for food. ACO has strong adaptability and global optimization search capability for complex multidimensional problems, and is widely used to solve combinatorial optimization problems and traveler's problems, etc.

The adaptability of initial population and algorithm convergence in traditional GA is poor. However, improving population diversity characteristics can enhance the solution space exploration ability of GA and accelerate convergence speed. The ACO algorithm has a positive feedback mechanism and initialization for fast convergence. The use of ACO in the initial initialization of GA can lead to the discovery of more optimal solution sets through the iteration of ant colony, thereby improving the quality of the GA solution space. This results in an improved initial population of GA with a high degree of adaptability, ultimately enhancing the convergence speed of the algorithm.

The probability $p_{ij}^k(t)$ of transferring ants between different attractions is calculated in Equation (13). In Equation (13), $\tau_{ij}(t)$ denotes the pheromone and t denotes the moment when the ants leave the pheromone. α denotes the importance of the pheromone and β denotes the heuristic factor. The ants use greedy rule to plan the path when β is large, and when β is small, the ants plan the path based on the pheromone. $allowed_k$ denotes the attraction that the ants have not yet visited, and $\eta_{ij}(t)$ denotes the degree of expectation of the ants from attraction i to attraction j.

$$p_{ij}^k(t) = \begin{cases} 0 \text{ ,} else \\ \dfrac{\left[\tau_{ij}(t)\right]^{\alpha} \cdot \left[\eta_{ij}(t)\right]^{\beta}}{\sum_{j \in allowed_k} \left[\tau_{ij}(t)\right]^{\alpha} \cdot \left[\eta_{ij}(t)\right]^{\beta}} & j \in allowed_k \end{cases} \tag{13}$$

The pheromone remaining on the path is updated after the ant has traveled to all the attractions, as shown in Equation (14). In Equation (14), ρ denotes the volatilization of pheromone and $\Delta\tau_{ij}(t)$ denotes the pheromone increment after iteration.

$$\begin{cases} \tau_{ij}(t+n) = (1-\rho) * \tau_{ij}(t) + \Delta\tau_{ij}(t) \\ \Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^{\ k}(t) \end{cases} \tag{14}$$

The calculation process of $\Delta\tau_{ij}(t)$ is shown in Equation (15). In Equation (15), Q denotes the pheromone intensity and L_k denotes the path length of the k th ant through all the attractions.

$$\Delta\tau_{ij}(t) \begin{cases} \dfrac{Q}{L_k} & tour(i,j) \in tour_k \\ 0 \; else \end{cases} \tag{15}$$

The crossover and mutation operations determine the diversification and evolutionary potential of the offspring individuals. To enhance population fitness and improve solution accuracy in GA attraction path planning, this study aims to improve GA's genetic operation. The adaptive crossover operation reduces the crossover probability for high fitness individuals to retain good individuals, and increases the crossover probability for low fitness individuals to accelerate new individual generation. The study utilizes adaptive crossover operation to improve GA, and the adaptive crossover probability p_c is calculated in Equation (16). In Equation (16), $f^{'}$, $f_{\max}$, $f_{\min}$, f_{avg} denote the individual fitness value, maximum, minimum, and average, respectively. k_1, p_{c1} are random numbers.

$$\begin{cases} p_c = p_{c1} - k_1 \dfrac{f^{'} - f_{avg}}{f_{\max} - f_{\min}} & f^{'} \geq f_{avg} \\ p_c = p_{c1} & f^{'} < f_{avg} \end{cases} \tag{16}$$

The final study used a local search algorithm 2-optimization (2-opt) method to optimize all paths in the population. The gene segments of the chromosomes are randomly flipped to generate new path planning solutions to determine whether the planned paths are optimized or not. The entire workflow of Hybrid Improvement Genetic Algorithm (HIGA) is shown in Figure 7. The 2-opt local search algorithm addresses the issue of lower search efficiency and longer solution times in the late GA evolutionary algorithm, while also enhancing the GA's local search capability.

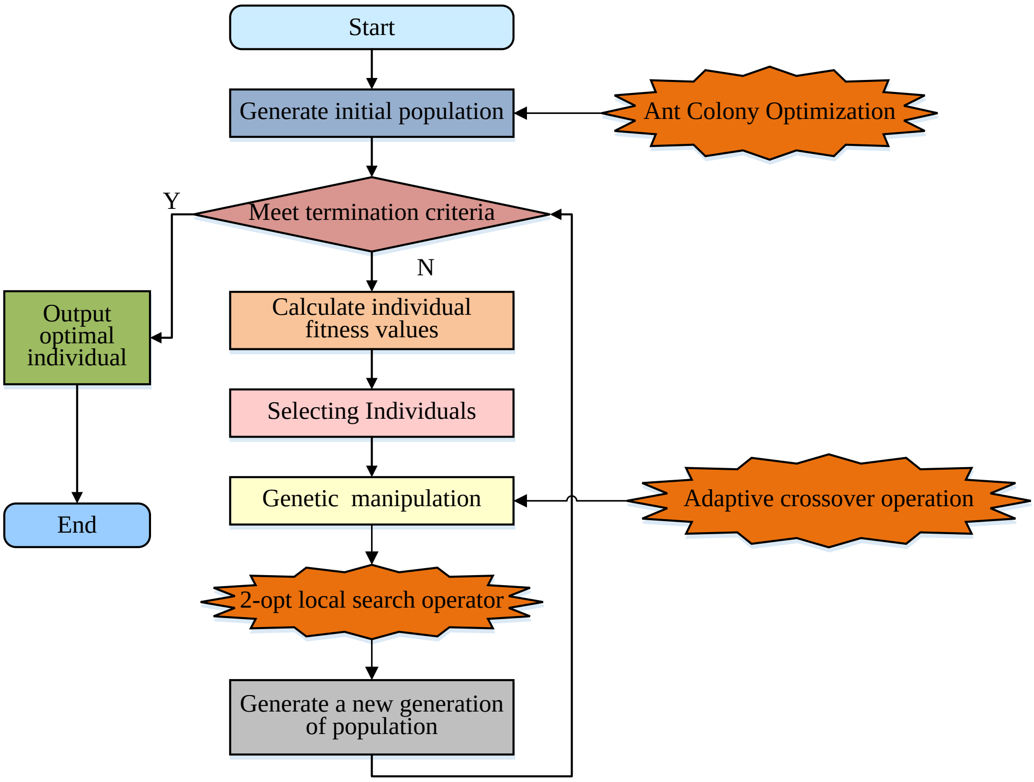


Figure 7: Workflow diagram of hybrid improved GA

4 Performance testing and application analysis of digital travel recommendation and route planning models

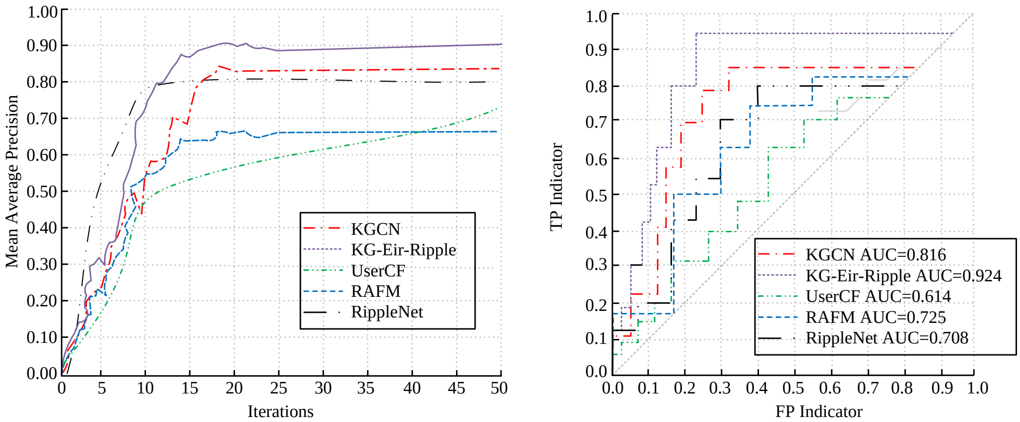
The study created several performance test experiments and ST application effect analysis tests to validate the utility of the travel RP and tourist attraction RM models built on RippleNet with enhanced GA.

4.1 Performance testing of recommendation modeling for tourist attractions by integrating knowledge graph and deep learning

The ml-100k, Deep Fashion, Jester, Book-Crossings, Last.fm, and Wikipedia datasets are selected to test the performance of the RM designed for the study. Ml-100k dataset contains 1,682 movies as well as 943 user movie ratings data. The Deep Fashion database contains a large number of fashion merchandise images and labels that can be used for research on image recognition and fashion recommendation techniques. The Jester dataset contains 6 million ratings of 150 jokes, which can be used for sentiment analysis and user preference prediction. The Book-Crossings dataset contains 90,000 user ratings and labeling data for books. Last.fm dataset contains music playback records and user preference data that can be used for research on music recommendation systems. Wikipedia contains text datasets on various topics, which can be used for tasks such as text categorization, entity-relationship extraction, and GA construction. After choosing the necessary data for the trials, the dataset is uniformly and randomly split into training and test sets at a ratio of 9 to 1.

The research-designed KG-Eir-Ripple RM with RippleNet, KG Fusion Graph Convolution Network (GCN) with KGCN model, UserCF based on UserCF and Recommendation Algorithm Based on Factorization Machine (RAFM). The experiment employs models that are all implemented using the Pytorch framework. The various experiments are conducted three times, with the average of the three outcomes serving as the final experimental result.

First, the experimental findings are displayed in Figure 8, which compares the Mean Average Precision (MAP) and Receiver Operating Characteristic curve (ROC) of several RMs. Recommender system suggestion ranking is measured by MAP, which also integrates precision and recall metrics to assess the model's performance across a range of categories in a more thorough manner. A higher MAP indicates that the system is able to find more relevant recommendation categories in the recommendation process and has a stronger sensitivity to the ranking of recommendation results. ROC describes the relationship between the rate of true cases and the rate of false positive cases under different thresholds of the model. The area created by the ROC and the axes is known as the Area Under the Curve (AUC). AUC has a value between 0 and 1, where 1 denotes flawless classification and 0.5 denotes random categorization. The higher the AUC value, the more comprehensively the model performs. In Figure 9(a), the MAP value of KG-Eir-Ripple RM reaches 0.90, and the MAP values of KGCN and RippleNet finally converge in the range interval of 0.80-0.85, and the research design improvement strategy achieves obvious effects. The MAP value of UserCF and RAFM only reaches about 0.70, which indicates that the recommendation method based on GA and deep learning is superior to collaborative filtering and factorization. In Figure 9(b), the ROC curve of KG-Eir-Ripple RM is located at the top of the coordinate axis, and the AUC value reaches 0.924. Under the same experimental environment, the AUC value has an obvious gap with other models. Additionally, the model performs at a higher level overall.



(a) MAP (b) ROC

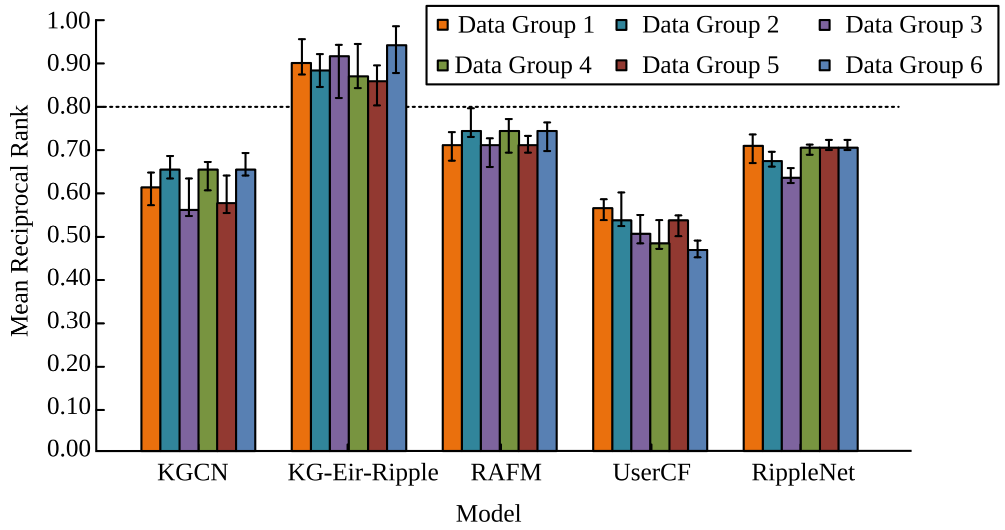
Figure 8: Comparison of accuracy and AUC values of different recommendation models

The results of other performance metrics of different RMs are shown in Table 2. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are the metrics to measure the deviation between predicted and actual values. MAE is more robust to outliers, while RMSE is more sensitive to large errors, and the two metrics can be evaluated in a comprehensive way. R-squared can indicate the degree of explanation of the model to the data variance, which can be used to evaluate the model fitting goodness of fit. Huber loss combines the advantages of MAE and mean square error, and has stronger robustness to outliers. It can be used as a loss function evaluation index to characterize the model fitting effect. Combining MAE, RMSE, and R-squared metrics can further synthesize and evaluate the recommended performance of RM. In Table 2, the KG-Eir-Ripple model takes better values than the other four RMs on four different metrics. The MAE and RMSE error metrics take lower values, with the MAE taking values lower than 0.40, and the lowest value being 0.316, and the RMSE taking values lower than 0.30, and the lowest value being 0.247. The other models take values higher than 0.40 for both error metrics on the different datasets, with the highest value being 0.601 for the RAFM model on the Wikipedia dataset for the MAE metric. 0.40, and the highest value taken by the RAFM model on the Wikipedia dataset reaches 0.601 for the MAE metric. The KG-Eir-Ripple model takes a larger value for the R-squared metric, and the lowest value reaches 0.844. The Huber loss value is the smallest, and the lowest value is 0.215. Combined with the error metrics, it is considered that KG-Eir-Ripple model performs optimally. Ripple model has optimal performance.

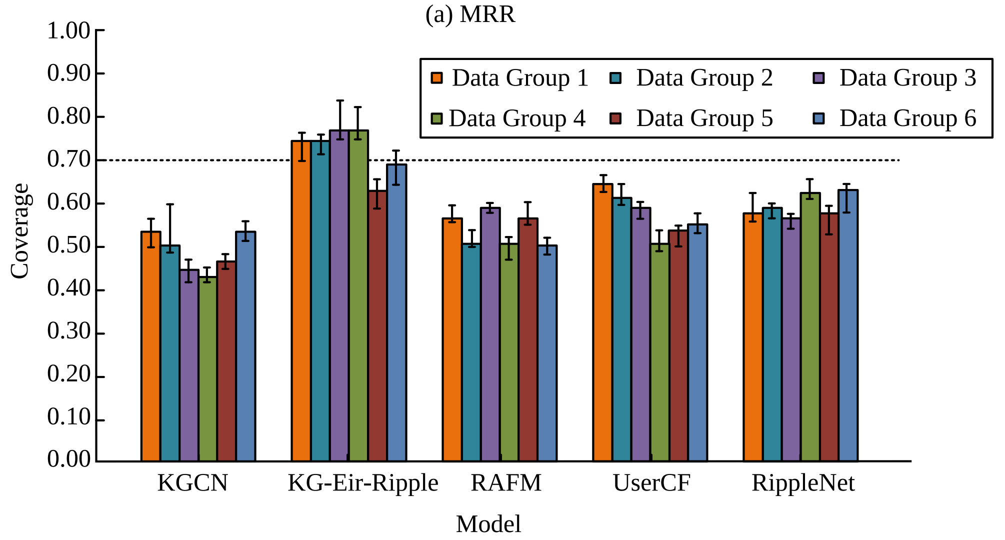
Table 2: Comparison of recommendation prediction performance of different recommendation models

Model	ml-100k	Deep Fashion	Jester	Book-Crossings	Last.fm	Wikipedia
KG-Eir-Ripple	MAE	0.412	0.426	0.376	0.394	0.316
	RMSE	0.259	0.247	0.267	0.254	0.267
	R-squared	0.846	0.863	0.844	0.871	0.869
	Huber loss	0.215	0.310	0.287	0.294	0.264
KGCN	MAE	0.547	0.543	0.574	0.569	0.560
	RMSE	0.348	0.347	0.394	0.406	0.375
	R-squared	0.743	0.706	0.784	0.701	0.763
	Huber loss	0.354	0.467	0.365	0.431	0.475
RippleNet	MAE	0.423	0.469	0.478	0.513	0.544
	RMSE	0.420	0.413	0.520	0.544	0.398
	R-squared	0.703	0.694	0.675	0.701	0.722
	Huber loss	0.462	0.464	0.484	0.468	0.473
UserCF	MAE	0.586	0.613	0.564	0.547	0.598
	RMSE	0.461	0.467	0.476	0.468	0.501
	R-squared	0.651	0.633	0.674	0.645	0.638
	Huber loss	0.514	0.533	0.574	0.495	0.501
RAFM	MAE	0.525	0.514	0.522	0.567	0.601
	RMSE	0.436	0.474	0.463	0.501	0.472
	R-squared	0.682	0.713	0.641	0.647	0.682
	Huber loss	0.641	0.515	0.547	0.555	0.613

The statistical results of Mean Reciprocal Rank (MRR) and coverage rate metrics for different RMs are shown in Figure 9. The MRR metrics emphasize the sequential and positional relationship of recommended attractions when presented to the user, and measure the ranking of the recommendation results and the reasonableness of the ordering. The coverage rate chosen for the study includes the recommendation coverage rate and the category coverage rate, which measures the proportion of all attractions covered by the recommendation system and the proportion of recommended attractions to all attractions. In Figure 9(a), the KG-Eir-Ripple model has the largest MRR values across the different datasets, all above the 0.80 take level. A distinct advantage over the other models can be shown in Figure 9(b), where the combined coverage of the KG-Eir-Ripple model surpasses the 0.70 taking threshold. It is evident that this model produces recommendations that perform better in terms of comprehensiveness and sorting.



(a) MRR



(b) Coverage

Figure 9: Comparison of coverage and MRR of different recommendation models

In the comprehensive analysis, the KG-Eir-Ripple model demonstrates the best performance in terms of RMSE, MAE, ROC, mAP, MRR, and coverage metrics. KGCN, a fusion model of KG and Graph Convolutional Neural Networks, shows a more homogeneous performance design compared to the KG-Eir-Ripple model, similar to RippleNet. However, KGCN takes into account the importance of user-item relationships, while RippleNet incorporates interaction information. However, the research design of KGCN effectively combines the advantages of RippleNet and RippleNet, emphasizing the importance of item relationships. RippleNet incorporates interaction information. However, the KG-Eir-Ripple model, which takes into account the implicit relationships and interactions between the user and the item, effectively combines the advantages of RippleNet and KGCN. This improves the recommendation effect and results in optimal performance metrics and quality of recommendation measures. In comparison to the KG-Eir-Ripple model, the performance design of UserCF vs. RAFM performs worse due to inherent defects such as the cold-start problem, data sparsity, and lack of interpretability. The study's model utilizes the item representation enhancement module to improve the semantic information of KG, resulting in significant improvements in the MRR and coverage values of the recommendation effect evaluation metrics.

4.2 Performance test of improved GA tourist attractions path planning model

The research designed HIGA is compared with the traditional GA and ACO optimization algorithms. The TSPLIB dataset from the database Traveling Salesman Problem Library is selected as the research experiment dataset. TSPLIB is a dataset for storing and sharing Traveling Salesman Problems and contains various instances of Traveling Salesman Problems of different sizes and structures, which include information such as city coordinates, distance matrices, and best-known solutions. The pheromone volatilization factor of ACO is set to 0.1, the information heuristic factor α is set to 1, and the expectation heuristic factor β is set to 5. The probability of variation of GA is set to 0.04.

First, the experimental findings are displayed in Figure 10 along with a comparison and analysis of the Hypervolume Indicator (HV) and Inverted Generational Distance (IGD) of several optimization strategies. A multi-objective optimization problem's performance can be calculated using the HV indicator, which can also be used to assess the algorithm's Pareto-front solution quality. The performance of the solution set as well as its homogeneity and diversity are all improved with increasing HV values. The IGD index can be used to calculate the difference between the algorithm's generated approximate Pareto front and the real Pareto front; a smaller index means that the algorithm's generated approximate Pareto front is closer to the real Pareto front and performs better. The performance of the multi-objective optimization technique can be jointly assessed by IGD and HV. In Figure 10(a), the HIGA has the highest curve of HV metrics, fluctuating in the range of 0.80-0.90, and the obtained solution set is better than the traditional GA and ACO algorithms in terms of diversity and uniformity. In Figure 10(b), the IGD curve of the HIGA converges around the minimum value of 0.10, which is significantly different from that before the algorithm improvement. It can be seen that the GA improvement strategy designed by the study has an effective improvement effect on the accuracy of the solution set.

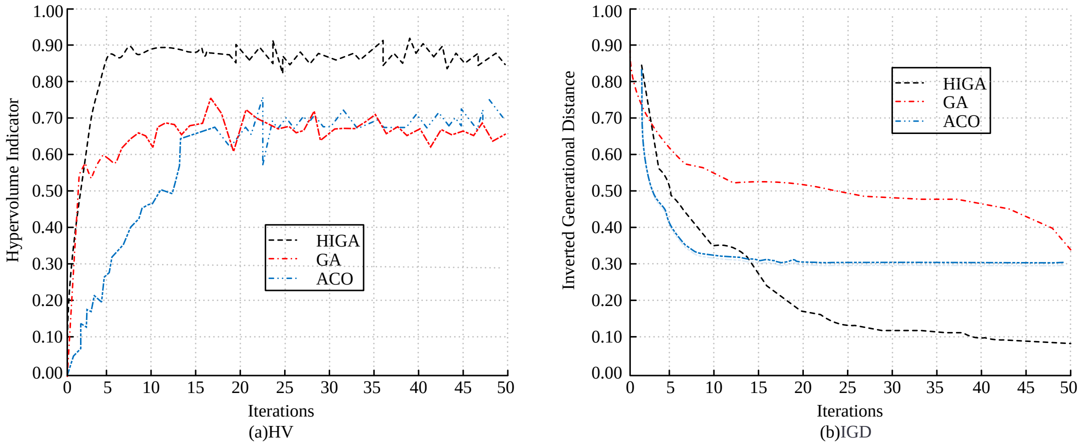


Figure 10: Comparison of HV and IGD for different multi-objective optimization algorithms

The Eil51 instance in the TSPLIB dataset is selected for analysis to evaluate the algorithm's optimization seeking ability before and after improvement. Additionally, the evaluation index used is population fitness, and Figure 11 displays the outcomes of the experiment. Figure 11(a) and (b) compare to show that, while the GA prior to the improvement must be close to the maximum population fitness in the middle of the iteration, the improved HIGA can make the average population fitness close to the maximum population fitness at the beginning of the iteration. The algorithm has been enhanced to improve population fitness, global optimal solution search, and fitness ability without the need for repeated iterations. The initialized population and adaptive crossover operation of HIGA are properly designed.

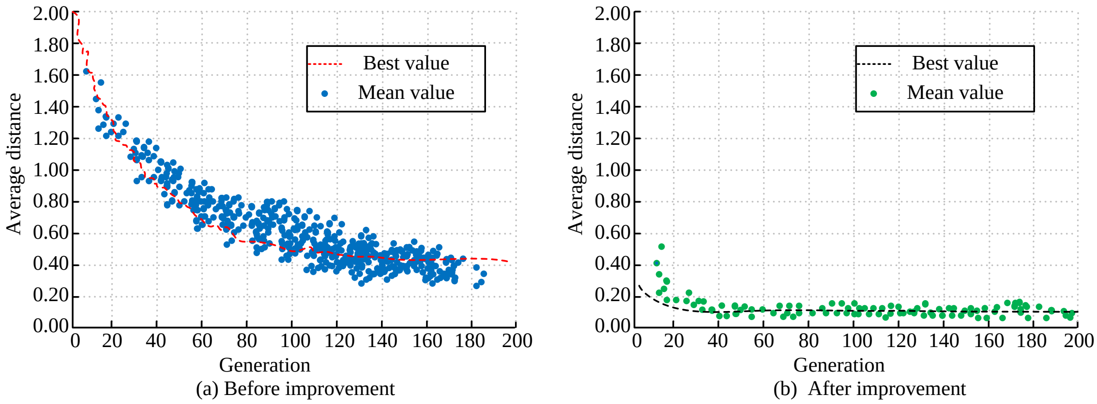


Figure 11: Comparison of population fitness evolution before and after GA improvement

The eil76 instance and oliver30 instance in the TSPLIB dataset are selected for path planning analysis, and the path planning effect before and after the improvement is shown in Figure 12. In Figure 12(a), for the instance analysis with fewer cities, the traditional GA can realize clearer path planning, and the initial path planning has achieved better results. The planning outcomes of the enhanced GA for pathways have not altered substantially as compared to Figure 12(b), and both path planning outcomes are applicable. However, in Figure 12 (c), when the number of cities rises and the distance of cities increases, the city traversal paths planned by the traditional GA are cross-mixed, and the city traversal has more cases of duplication and omission. In Figure 12(d), the improved GA still maintains better path planning effect, there is no cross-route, duplication or omission of travel between cities, the traversal path is clear, and the total length of the path is shorter. It can be concluded that the improved HIGA solves the traveler problem with a clearer and more accurate solving capability.

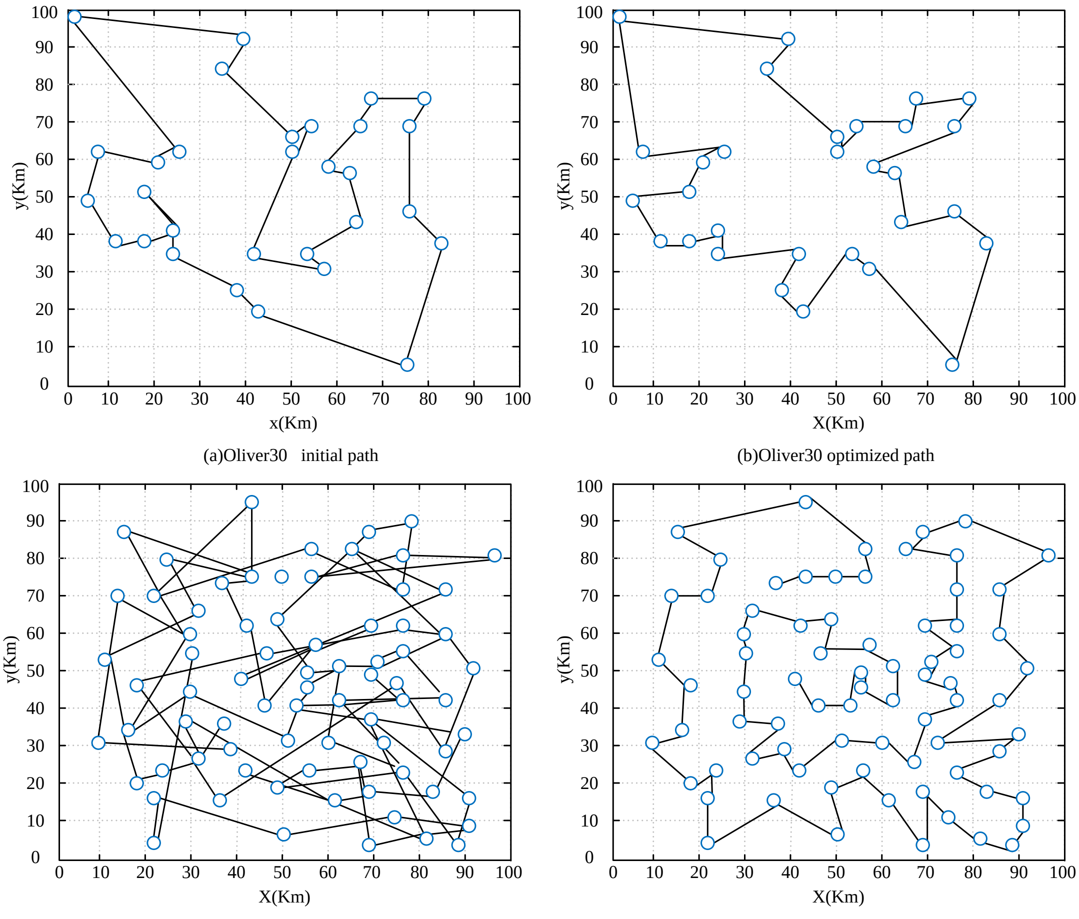


Figure 12: TSPLIB dataset instance path planning effect

4.3 Effectiveness of tourism recommendation and attraction route planning model application

The RM and path planning model designed by the study is applied to the actual ST analysis project, and the recommendation and planning effects of the model are analyzed. Taking travel expenses, time, and hotness of attractions into consideration, Beijing, a first-tier city in China, is selected as a pilot for ST analysis, and the distances between different attractions are obtained through Gaode Map. Detailed descriptions and user ratings of the attractions were obtained using major travel platforms.

Normalized Discounted Cumulative Gain (NDCG) and Hits Ratio (HR) are selected as the evaluation metrics of attraction recommendation results. NDCG evaluates the performance of the recommendation system by taking into account the relevance of the recommendation results and the ranking order, and combines the idea of discounted cumulative gain to evaluate the results of RM. TAn increased value denotes a stronger model recommendation effect. The "#" in the k-indicator denotes the truncation of the results, meaning that the NDCG values are computed within the range of the first k recommendation outcomes. HR can measure the proportion of correct hits in the recommendation results, i.e., the proportion of users clicking on the recommendation results, and HR and NDCG jointly evaluate the attraction recommendation effect. In Table 3, with the expansion of the range of recommendation results, the HR and NDCG indicators of different models show an increasing trend, but under the same recommendation conditions, the KG-Eir-Ripple model has the best recommendation effect on attractions. When the recommendation result reaches 20, the HR of KG-Eir-Ripple model is 94.16%, and the NDCG reaches 76.26%, the recommendation result achieves a relatively excellent performance, which is suitable for the tourists' needs.

Table 3: Comparison of recommended tourist attractions

Model	Evaluating indicator	KG-Eir-Ripple	KGCN	RippleNet	UserCF	RAFM
#3	HR	46.13%	40.65%	37.62%	36.28%	34.88%
	NDCG	32.42%	26.45%	24.13%	28.27%	22.23%
#5	HR	53.04%	46.26%	41.26%	42.64%	45.16%
	NDCG	45.37%	40.26%	39.45%	35.16%	38.14%
#7	HR	74.26%	62.16%	66.15%	61.74%	58.44%
	NDCG	49.32%	41.26%	42.56%	40.15%	42.16%
#10	HR	79.45%	66.81%	69.16%	67.16%	69.46%
	NDCG	56.45%	45.56%	44.67%	42.86%	46.64%
#15	HR	84.16%	72.16%	73.46%	75.56%	76.62%
	NDCG	62.16%	49.15%	48.76%	49.26%	50.26%
#20	HR	94.16%	83.26%	84.23%	87.26%	84.16%
	NDCG	76.26%	64.46%	67.26%	67.96%	69.16%

Thirty volunteers were recruited to participate in the experiment and divided into experimental and control groups, choosing the same attractions to visit, the experimental group using the path planning model designed by the study, and the control group practicing independent path planning. To assess the efficacy of path planning between attractions, three criteria were selected: route fluency, RP rationality, and comprehensive satisfaction. The scoring outcomes are displayed in Figure 13. The experimental group's three scores are all greater than the control groups in Figure 13(a), and the median level is above 65 points. It can be seen that after the planning of the research design model, the length of the route, the time of the tour, the choice of transportation mode and the connection between attractions are more reasonable, the route is more fluent, and a higher satisfaction rating is obtained.

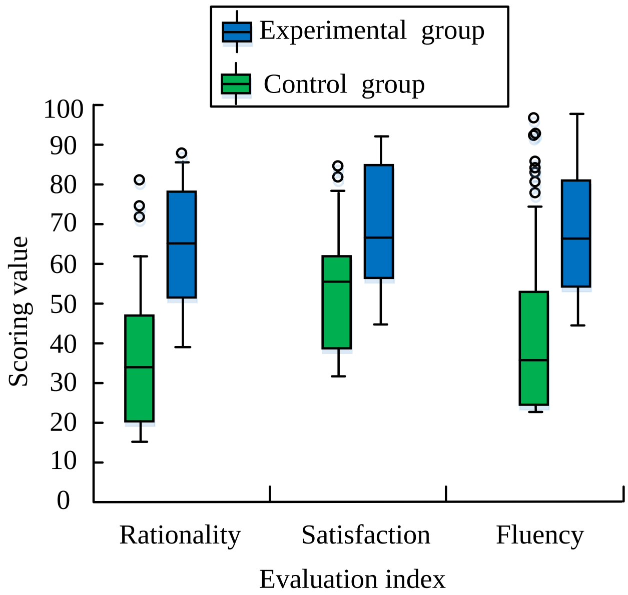


Figure 13: Comparison of tourist attraction route planning and evaluation

5 Discussion

To achieve the intelligent development level of ST and align with the trend of personalized and customized tourism services, this study presents digital tourism research that integrates tourist attraction recommendations and RP. A model for recommending tourist attractions has been developed using deep learning technology and KGs. The RippleNet item representation enhancement module considers the user's interaction relationship and implicit information between the user and the attraction. This module mines hidden information between the user's historical interests and the attraction, which improves the accuracy and personalization of recommendations. Furthermore, a KG is a type of structured data graph that contains a wealth of semantic relationships and entity attribute information. By incorporating the KG related to tourist attractions into the recommendation model, the connections and characteristics between attractions can be better understood. This will provide travelers with more accurate and diverse recommendation results. The study combines the strengths of existing research shown in Table 1 and considers the importance of interactive relationships and personalized needs in digital tourism. The study discusses the current state of research and proposes a RP model that combines multiple technologies. The model uses hybrid intelligent optimization algorithms, specifically the GA and ACO algorithms, to simplify the model and reduce the amount of calculations required. This improves the efficiency of RP. However, the improved GA still has potential application limitations. The algorithm may fall into a local optimal solution or slow down convergence speed when the initial population quality and genetic operation strategy are insufficient. Additionally, the algorithm's performance may not reach optimal levels due to the complexity of the planning problem itself. To enhance the adaptive ability of the initial population and improve the convergence speed and global search ability of the algorithm, it is recommended to repeatedly utilize the ACO algorithm, adaptive crossover operation, and local search algorithm during the planning process. The algorithm's limitations should be addressed by adjusting parameters, optimizing operations, and improving the matching of planning problem characteristics.

The research proposes a model for recommending tourist attractions and planning routes in the field of intelligent tourism. This enriches the success of research and has reference significance for future tourism management and development. Based on the planning results, it is possible to create a digital tourism experience that integrates tourist attraction recommendations and RP. The recommendation model provides personalized results that are tailored to the user's interests, while the RP model considers external constraints and personal preferences to minimize path redundancy and wasted time, resulting in an efficient travel experience. On the other hand, digital models for travel recommendations and RP can save time and material costs for tourism management, while also facilitating tourism business planning and marketing.

Finally, based on the results of this research, future studies can consider additional factors for more accurate recommendations and planning, such as travel time, passenger flow, weather, and holidays. This will lead to more comprehensive and personalized recommendations, especially given the rapid development of tourism demand and technological capabilities. In addition, future research can enhance cross-domain cooperation to improve the effectiveness and application of digital travel recommendation and RP models.

6 Conclusion

Continuous research and design of RP for tourist attraction recommendation and development of ST is necessary for tourism service providers to improve tourism experience and industrial competitiveness. However, there are many tourist attractions, and the on-site research method is time-consuming, extensive, and expensive, which leads to very cumbersome attraction recommendation and RP. To improve the digitization of ST, the study is based on the GA recommendation method and the RP method of GA to improve the research. The experimental results revealed that the research-designed KG-Eir-Ripple model took higher values of MAP and AUC, MAE and RMSE converged to the lowest value, while the R-squared metric was 0.844 and the Huber loss was as low as 0.215, and all the metrics comprehensively and comprehensively verified the superiority of the model. On different recommendation datasets, the KG-Eir-Ripple model had the largest MRR value, the comprehensive coverage was higher than 0.70, and the ranking and comprehensiveness of the recommendation results were superior. In addition, the HV indicator of HIGA fluctuates between 0.8 and 0.9, and the IGD was converged to 0.1, and the improvement strategy helps to improve the accuracy of the solution set. And the evolutionary curve of population fitness of HIGA performed better, and it was applied in TSPLIB dataset instance path planning with better results, no crossing of planning paths, and better traversability. In the actual attraction recommendation effect, when the number of recommendation results was 20, the HR of KG-Eir-Ripple model was 94.16%, and the NDCG reached 76.26%, with better recommendation effect. Additionally, the experimental group's path planning score had a much higher user satisfaction rating than the control groups. This research helps to promote the development of digital informatization in the tourism industry, and the attraction recommendation and RP model facilitates the travel of tourists, which is of positive significance for the maintenance of the competitiveness and innovation of the tourism industry. However, the RP for GA should also further consider the

RP within attractions, which can be the focus of future research work.

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