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Computer-Aided Design AND APPLICATIONS

Customer Behavior Analysis and Reinforcement Learning Application in Tourism Service Design

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Abstract. The improvement of tourism service design requirements is the inevitable result of the interaction between the tourism industry and the individual needs of customers. The traditional design method lacks objectivity and science and can not fully meet the customer's preference and help the customer choose a better travel mode. Intelligent technology should break the restrictions of tourism service design so that it can better realize the analysis of customer behaviour. To better improve the accuracy of tourism service design, this paper combines CAD and reinforcement learning to build an intelligent tourism service design model and conducts customer behaviour analysis and service design optimization through deep reinforcement learning. The experimental results show that compared with other models, the proposed model has a good performance of tourism interest points and tourism route recommendation and good stability. The experimental results show that the model can effectively analyze customer characteristics and customer travel behavior, and recommend tourist attractions and travel routes that combine customer needs and preferences based on the analysis results to avoid repeating routes in the same area. At the same time, the accommodation points recommended by this model can take into account tourism needs and customer preferences to enhance customer's sense of travel experience.

Keywords: Reinforcement Learning; CAD; Tourism Services; Behavior Analysis; Personalized Recommendation
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1 INTRODUCTION

With the improvement of social and economic levels and the evolution of personal consumption concepts, tourists' expectations for tourism services have gone beyond the traditional sightseeing level and instead focused on the depth of tourism experience and excellent quality of service. They are no longer satisfied with a casual tour but are eager to gain personalized and tailor-made service experiences during the journey to fit their unique interests and individual needs [1]. At the same time, with the rapid progress of cutting-edge technologies such as big data, cloud computing, artificial intelligence and the Internet of Things, the intelligent transformation of tourism services has ushered in unprecedented opportunities. The application of these technologies has endowed tourism enterprises with powerful data analysis capabilities, enabling them to gain in-depth insight into tourists' individual needs and behavioural habits. Based on this, tourism companies can accurately customize service solutions, provide tourists with both intimate and intelligent travel experiences, and meet the unique expectations of each tourist. Based on this, the intelligent and personalized development of tourism service design has become an inevitable trend. In traditional tourism services, it is often difficult for tourists to obtain comprehensive and accurate tourism information. Tourists often need to spend a lot of time and energy booking tourism products and inquiring about tourism information. At the same time, due to the complicated process of tourism services, inconsistent service standards, unreasonable use of tourism resources and other reasons, tourists often difficult to obtain a good tourism experience [2]. Compared with traditional tourism services, intelligent tourism service design has significant advantages in improving service quality, optimizing resource allocation, solving information asymmetry, etc., and can effectively solve problems existing in traditional tourism services. In addition, tourism preference is highly subjective, that is, different tourists have great individual differences due to social relations, dietary preferences, interest points, accommodation requirements and other factors, so many researchers try to improve the accuracy of tourism service design through intelligent technology. Some researchers mine customer behaviour data and conduct correlation analysis through data mining technology and correlation algorithms, and recommend corresponding services to customers based on the analysis results. Other researchers recommend interesting scenic spots, restaurants and other places for customers based on information such as text semantics and the location of social networks. However, these algorithms all have a high constraint on the access time of customers and are greatly affected by the sparse factors of data sets. Therefore, there are problems caused by cold start and lack of effective data in many recommendations, which reduces the accuracy of personalized recommendations [3].

CAD reinforcement learning, as a branch of artificial intelligence, has opened up a new path for the intelligent application of CAD software by allowing machines to learn and optimize decision-making processes in large amounts of data. BIM technology creates highly detailed 3D interactive models that not only accurately express the physical characteristics of buildings, but also integrate historical, cultural, and restoration information, providing powerful tools for the digital protection and management of heritage buildings. Customer behaviour analysis, as a key means of understanding market demand and optimizing service experience, plays an increasingly important role in tourism service design. For example, based on real-time feedback and behavioural data from tourists, CAD reinforcement learning algorithms can dynamically adjust the path planning, visual effects, and interaction methods of virtual guides to ensure that each tourist receives the best experience [4]. On this basis, combined with point cloud data and other real-world capture technologies, HBIM further enriches the dimensions of the model, enabling it to vividly reproduce the original style and transformation process of historical buildings. This interactive and rich virtual 3D model not only enhances public awareness of heritage value but also opens up new avenues for cultural tourism experiences [5]. In tourism service design, CAD reinforcement learning can be applied to optimize virtual navigation systems, design immersive experience scenarios, and innovate interactive information displays. Through technologies such as big data analysis and user profiling, it is possible to accurately grasp tourists' preferences, behaviour patterns, and decision-making processes, thereby customizing the design of tourism products and services. Taking the Zainal historic house in Jeddah, Saudi Arabia as an example, this study integrates BIM, customer behaviour analysis, and CAD reinforcement learning technology [6]. Tourists can not only understand the historical background, structural features, and restoration process of buildings through highly realistic 3D models, but also customize tour routes based on personal interests, participate in interactive games based on real historical events, and even experience historical scenes firsthand using VR/AR technology. In the context of heritage tourism, this means that personalized guide paths, interactive experiences, and information push can be provided based on tourists' interests, knowledge backgrounds, and interaction habits [7]. It can design an intelligent tourism experience solution that integrates education, entertainment, and interactivity. At the same time, the system will continuously optimize service processes based on real-time feedback and behavioural data from tourists, ensuring that each tourist can receive a personalized and high-quality travel experience.

To gain a deeper understanding of the authenticity construction mechanism in VR tourism experiences, some scholars conducted in-depth interviews with 28 representative interviewees and used thematic analysis to analyze the collected data in detail. In this framework, customer behaviour analysis plays a crucial role. By capturing and analyzing tourists' behavioural patterns, preference changes, and emotional responses during VR tourism experiences [8]. For example, using CAD reinforcement learning technology, the system can automatically learn and optimize interactive elements in VR scenes. Through a data processing method that combines induction and deduction, three core themes were extracted and further refined into six sub-themes, which together form a multidimensional framework for the perception of VR tourism authenticity. It can more accurately grasp the real needs and expectations of tourists, providing the scientific basis for the personalized design of tourism services. In addition, CAD reinforcement learning has also promoted the continuous iteration and innovation of VR tourism experiences [9]. By analyzing feedback data from tourists, the system can continuously identify and correct shortcomings in the experience. At the same time, explore new design ideas and interactive methods to stimulate tourists' curiosity and sense of participation. This data-driven intelligent design process. Visual presentation and narrative structure are used to better match tourists' personalized preferences and enhance the authenticity and immersion of the experience. Not only has it improved the quality and efficiency of VR tourism experiences, but it has also brought unprecedented innovative vitality to the field of tourism service design [10].

To improve the accuracy of tourism service design, this paper combines CAD and reinforcement learning to build an intelligent tourism service design model, realizes the construction of a virtual tourism space model through a CAD system, and analyzes customer behaviour with deep reinforcement theory. According to the analysis results, personalized recommendation of tourism interest points and travel routes is realized, and the tourism service experience of customers is improved. The innovation of this paper is to apply CAD reinforcement learning technology to the design of tourism services and to achieve accurate analysis and real-time response to customer behaviour by building an intelligent service system, to promote the intelligent and personalized development of tourism services.

2 RELATED WORK

Tourism service design has always been an important component of the tourism industry. In the past, tourism service design was based on data analysis obtained from market surveys and customer questionnaires. Due to the relatively small amount of data obtained and the high subjectivity, there is often a certain gap between the analysis results and the actual situation. To improve the quality of tourism service design, Lê and Nguyen [11] introduced regression models into data analysis to analyze the correlation and mutual influence between different influencing factors. Although this method improves the accuracy of data analysis to some extent, the analysis results obtained are local due to limitations in data conditions. With the development of intelligent technology, some tourism platforms use machine learning algorithms to combine users' historical behaviour data and real-time traffic information to recommend the best travel routes for tourists. This algorithm not only considers the popularity of tourist attractions and their preferences but also adjusts routes in real time to avoid traffic congestion, thereby improving travel efficiency and comfort. Lv et al. [12] analyzed the interaction between customer travel process and catering factors from the perspective of catering and optimized the catering structure of tourist attractions based on the analysis results. Some travel agencies improve cruise travel space and routes based on customer behaviour analysis results to enhance the customer travel experience. In terms of service processes, some tourism companies use tools such as service blueprints and customer journey maps to optimize their service processes. For example, a certain hotel determines the pain points and needs of guests in various aspects such as check-in, dining, and leisure by drawing a customer journey map. Based on this, Muniz et al. [13] redesigned the service process, including providing personalized accommodation experiences, convenient catering services, and abundant leisure and entertainment facilities. Some tourism companies have used big data technology to analyze the pain points of customers' travel accommodations, improving the environment of public areas and adding children's play areas. At the same time, in the accommodation room space, child beds, and mother and baby beds have been added to provide more comfortable and intimate living environments for more families.

CAD reinforcement learning technology can automatically optimize the design, interactive experience, and content presentation of tourism scenes based on these behavioural data, ensuring that metaverse tourism products can continue to attract tourists and improve user satisfaction and loyalty. The research by Oncioiu and Priescu [14] shows that metaverse tourism products and experiences have enormous potential to expand the boundaries of tourism resources and promote sustainable tourism development. By mining and analyzing massive amounts of data, it is possible to identify the real needs and potential interests of tourists, providing a scientific basis for personalized customization and precise marketing of tourism products. In this process, the deep integration of customer behaviour analysis and CAD reinforcement learning technology will further optimize tourism service design, ensuring that metaverse tourism products can accurately meet market demand and efficiently achieve sustainable development goals. By creating alternative, high-value-added resources in the virtual world, these innovations not only enrich the tourism experience but also significantly improve the economic benefits of tourist destinations, contributing new ways to achieving the Sustainable Development Goals (SDGs). It is crucial to follow the sustainable development goals of the United Nations World Tourism Organization in the development process of metaverse tourism products. This means that a balance between environmental impact, social inclusiveness, and economic benefits needs to be considered during the design phase to ensure the long-term sustainable development of the product. Sakao et al. [15] combined customer behaviour analysis with CAD reinforcement learning to more accurately evaluate the sustainability impact of different design schemes, thereby making more scientific and rational decisions. The application of customer behaviour analysis technology enables tourism service providers to gain a deeper understanding of tourists' behaviour patterns, preference changes, and consumption decision-making processes in the metaverse.

Shaheer and Carr [16] delve into how customer knowledge management (CKM) can be combined with customer behaviour analysis and CAD reinforcement learning techniques. This article reviews and reveals that tourism experience, as the core driving force for innovation and optimization of tourism products and services, contains extraordinary customer knowledge value. A CKM conceptual framework that deeply integrates with the concept of intelligent tourism has been developed, which carefully designs eight key processes to comprehensively guide the efficient management practices of DMOs in the era of intelligent tourism. On this basis, CAD reinforcement learning technology continuously optimizes the service model through machine learning algorithms, automatically adjusts service strategies, better meets the personalized needs of tourists, and improves the overall satisfaction and loyalty of the tourism experience. Jointly authorize destination management organizations (DMOs) to finely and intelligently manage tourism experiences, thereby promoting innovation in smart tourism solutions and the prosperous development of smart tourism destinations (STDs). Through practical verification, this framework has significant effectiveness and wide applicability in improving the quality of tourism services, enhancing the value of the tourism experience, and promoting the construction of intelligent tourism destinations. It not only enhances the local tourism bureau's keen perception and rapid response-ability to the dynamics of the tourism market but also promotes the transformation and upgrading of tourism services from "standardization" to "personalization" and "intelligence".

We can more accurately capture tourists' behaviour patterns, preference trends, and potential needs, providing strong data support and an intelligent decision-making basis for personalized design and continuous optimization of tourism services. The current application of CKM in this field is still insufficient, and its potential has not been fully tapped to support the development of intelligent tourism. By introducing customer behaviour analysis and CAD reinforcement learning techniques. With the increase in customers' personalized needs, some researchers have obtained the demand points of single tourism customers through massive data analysis, and provided corresponding customers with small-space accommodation environments and customized escort services, to reduce the time cost of customers' travel strategies and improve their sense of travel experience. Some researchers have also proposed corresponding tourism service designs for unique groups. For example, research and learning services can be provided for teenagers. In addition to Xia Liying's research and learning experience, in-depth research and learning tourism service plans can also be formulated according to customers' preferences and behaviours. In addition, some researchers have used the emotional model to analyze the travel motivation and emotional needs of customers, to provide more emotional service design for customers. With the development of virtual reality technology, some researchers have proposed the use of virtual reality technology to improve customer travel immersion. To sum up, at present, the application of intelligent technology in tourism service design is mostly to solve the pain points of tourism for customers in a certain field, which is a lack of systematicness and comprehensiveness. Therefore, the intelligent tourism service design model based on CAD reinforcement learning in this paper still has certain value in practical application.

3 CONSTRUCTION OF INTELLIGENT TOURISM SERVICE DESIGN MODEL

3.1 Customer Behavior Analysis Model

The tourism customer behavior analysis model aims to reveal the behavior rules, preferences, and trends of tourism customers by collecting, analyzing, and explaining their behavior data in the process of tourism. It includes two parts: customer characteristics and customer travel behaviour, which have mutual influence and are both affected by customers' own cultural level and social relations. At the same time, customer characteristics and customer travel behaviour will jointly determine the customer's travel purpose, travel interest and travel route selection, which is an important influencing factor for tourism service design. Figure 1 shows the schematic diagram of the tourism customer behaviour analysis model. This paper will use this model to analyze the characteristics and tourism behaviour.

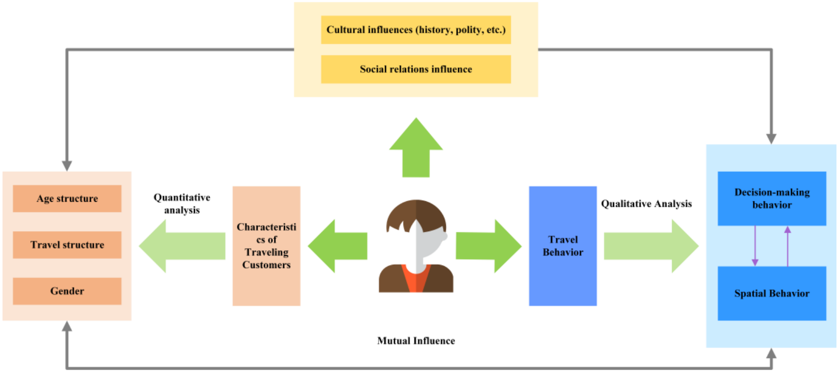

Figure 1: Tourism customer behavior analysis model.

In tourism service design, customer characteristics analysis is the premise of its design; that is, the result of customer characteristics analysis determines the customer group and market positioning of tourism service design and is the keynote of all service design. According to the tourism user behaviour analysis model combined with the survey results in recent years, customer characteristics mainly exist in the following manifestations, as shown in Table 1. In terms of age characteristics, it is mainly concentrated in the range of 22-35 years old and more than 60 years old; the two ranges of customers have a certain economic ability; the former is more inclined to explore the world, the latter is inclined to enjoy the world. Secondly, the ages are concentrated in the range of 10~18 years old and 36~45 years old; the two age ranges have a greater correlation, combined with the travel structure, it can be seen that the customers of these two age ranges are mostly family members. In terms of gender characteristics, women are less likely to travel than men due to the constraints of social and environmental conditions.

Customer characteristics	*section*	*Take up a proportion of*
Age characteristics	10 to 18 years old	17.6%
	19~35 years old	28.2%
	36~45 years old	15.7%
	46~59 years old	8.4%
	Over 60 years old	30.1%
Travel structure	Families with children	51.7%
	couple	20.3%
	Friend	22.9%
	By oneself	5.1%
sex	male	62.5%
	female	37.5%

Table 1: Analysis results of tourism customer characteristics.

The above customer characteristics determine the customer's travel mode, economic cost, time cost, travel motivation, etc., thus affecting the customer's travel decision-making behaviour. When time and economic conditions are guaranteed, customers will take their subjective preferences as the main basis for travel behaviour decision-making. However, decision-making behaviour is a psychological process with high complexity, which is influenced by many external environmental factors and completes the final behavioural decision under the influence of multiple factors. According to relevant studies, the travel motivation of tourism customers has a crucial effect on tourism behaviour.

3.2 Customer Travel Interest Point Recommendation Module Based on Deep Reinforcement Learning

According to the above tourism customer behaviour analysis model, this paper will select the data factors of the tourism interest point recommendation module according to the characteristics of customers and tourism behaviour. Due to the diversity of customer characteristics and tourism behaviour characteristics, customer characteristics will affect travel motivation and tourism behaviour will be realized according to the customer's travel preferences. This indicates that the interest points of tourism customers may have fixed patterns or diversified change patterns, as shown in Figure 2. It can be seen from the results that it is relatively easy for customers with fixed interest points to recommend travel interest points, while customers with fixed and diversified interest points have more interest points, but there are certain rules on the whole, and the difficulty in personalized recommendation is relatively low. However, the personalized recommendation of customers with changing interests has great difficulties; that is, it can not be considered accurate. Therefore, this paper will adopt the next point of interest recommendation model, that is, recommend the next travel project based on the current point of interest and behaviour of the tourist point customers, to ensure that the customer can always obtain the recommendation results with high accuracy.

Table 2 shows the data factors and related descriptions of interest points selected according to the customer behaviour analysis model.

Factor	*Instructions*
User preference	The user's personal preferences
Access	The sequence of points of interest accessed by the user

sequence	
Check-in time	The time the user accesses the point of interest
Geographical position	The current location of the user, the geographic location of the point of interest
Social relationship	The user's relationship in social activities (such as friendship, similar behaviour, etc.)
Text semantics	Textual characteristics of the user and points of interest (e.g., user's gender, age; Types of interest points, etc.)
Other context	Other factors that can affect the results of points of interest recommendations (such as weather, traffic, etc.)

Table 2: Data factors and related descriptions of tourism customers' interest points.

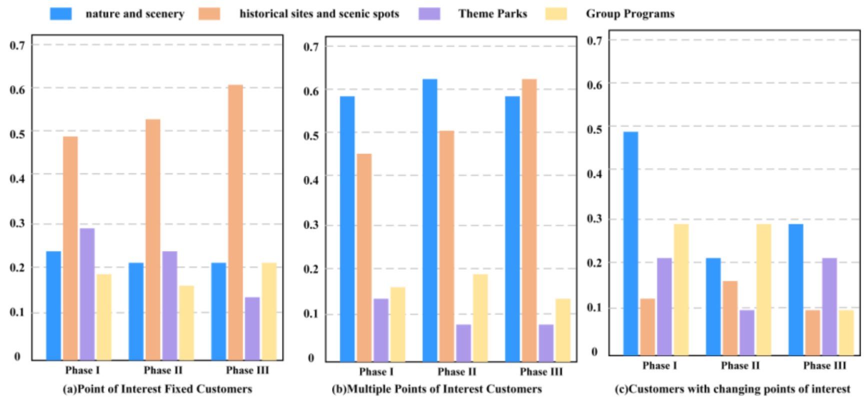

Figure 2: Part of tourism interest points to monotonous and diversified tourism customer display.

In the module of interest point recommendation, this paper uses deep Q network in deep reinforcement learning and the Actor-Critic model to realize user behaviour data analysis and next travel interest point recommendation. Posit QValue expressed as $Q(s,a;\theta)$ Its distribution is represented by a function as shown in (1):

$$Q(s,a) \approx f(s,a) \tag{1}$$

Where the state is represented as s, Action is expressed as a, and The neural network parameters are expressed as θ.

The formula for calculating the target value is shown in (2):

$$y = r + \gamma max_{a'} Q(s',a';\theta^{-}) \tag{2}$$

Where the discount factor is expressed as γ. The target network parameters are expressed as θ^{-}.

The loss function is shown in formula (3):

$$L(\theta) = \frac{1}{2}[Q(s,a;\theta) - y]^2 \tag{3}$$

In the actor-critic model, there are two main components: Actor and Critic. The Actor is responsible for generating the actions, and the Critic is responsible for evaluating the good or bad of those actions, i.e., estimating the action value function or state value function. Actors are usually optimized by a strategy gradient approach. The policy gradient theorem states that the updating direction of the policy parameters is the direction of the gradient of the policy parameters. For continuous action Spaces, this is usually expressed as (4):

$$\nabla_\theta J(\theta) = E_{\tau\sim\pi_\theta}[\sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t | s_t)\hat{A}_t] \tag{4}$$

Where the trajectory is expressed as τ, whose length is expressed as T, the advantage function is expressed as $\hat{A}_t$.

The dominance function is defined as shown in (5):

$$A^\pi(s_t, a_t) = Q^\pi(s_t, a_t) - V^\pi(s_t) \tag{5}$$

3.3 Personalized Travel Path Recommendation Module Based on Deep Reinforcement Learning

Tourism is a dynamic process; under normal circumstances, customers will first determine the main attractions, and as the center, spread around to supplement other tourist spots, or customers will choose tourist spots along the way to play. Failure to choose the right travel path will not only reduce the customer's sense of experience but also cause subsequent tourist attractions to be unable to proceed as planned. In addition, different customer choice travel modes, travel structure, economic cost, time cost, and other factors will affect the personalized recommendation of travel routes. Therefore, the timing and strategy of actual tourism behaviour and route selection should be fully considered. Based on deep reinforcement learning, this paper combines the Markov decision process, strategy, value function, and Q-learning algorithm to build a travel route recommendation module.

Let the Markov process include the environment state, the agent acting, the probability of the state performing the action to another state, and the reward value, which are described as (S, A, P, R). When the agent is at At step n, its state value function is shown in formula (6):

$$V_\pi(s) = \mathrm{E}\left[H_n \middle| S_n = s\right] \tag{6}$$

Where the strategy is denoted as π the current status is expressed as s The reward value is expressed as H_n Reinforcement learning requires the optimal strategy to maximize the expected return value.

The action value function is the Q function, as shown in formula (7):

$$q_\pi(s, d) = \mathrm{E}\left[H_n \middle| S_n = s, D_t = d\right] \tag{7}$$

Where the execution action is represented as D The current execution action is denoted as d Q The value of the function is denoted as the expected return of the action performed in the current state and its maximum value is obtained.

The decomposition of the state value function and action value function can be obtained according to the Bellman equation, as shown in formulas (8) and (9):

$$V_\pi(s) = \sum_d \pi(d|s) \sum_{h'} \sum_r p(s', r | s, d)[r + \alpha v_\pi(s')] \tag{8}$$

$$q_\pi(s, d) = \sum_{s', r} p(s', r | s, d)[r + \gamma v_\pi(s')] \tag{9}$$

Among them, γ Represents the discount factor.

In general, when making a route decision, a single agent may weaken the weight of customer preference due to other factors that are attractive to it, so that the planned route is not attractive to customers or there is a certain gap between the planned route and the original goal. Therefore, this paper increases the number of agents to three, corresponding to the direction choice, distance choice, and place choice in the choice of travel route. The new constraints are shown in formulas (10) and (11):

$$R_{n,m}=\begin{cases}1, \left|e^{DR}_{v_{n,m-1},v_{n,m}}-e^{DR}_{v_{n,m},v_{n,m+1}}\right|\neq 180^\circ \\ -1, \left|e^{DR}_{v_{n,m-1},v_{n,m}}-e^{DR}_{v_{n,m},v_{n,m+1}}\right|=180^\circ\end{cases} \tag{10}$$

$$f_6=\sum_{n=1}^{u^D}\sum_{m=1}^{N^P}R_{n,m} \tag{11}$$

Where the judgment on whether there is a return-back phenomenon on the route is expressed as $R_{n,m}$ In the whole process, the reward or punishment after the return of the route is expressed as f_6.

The objective summary of the direction selection task is shown in (12):

$$O_1=\theta_1 f_1+\theta_3 f_3+\theta_5 f_5+\theta_6 f_6 \tag{12}$$

The objective summary of the distance selection task is shown in (13):

$$O_2=\theta_1 f_1+\theta_2 f_2+\theta_3 f_3+\theta_4 f_4+\theta_5 f_5 \tag{13}$$

The objective summary of the location selection task is shown in (14):

$$O_3=\theta_1 f_1+\theta_3 f_3+\theta_5 f_5 \tag{14}$$

4 ANALYSIS OF EXPERIMENTAL RESULTS

4.1 Experimental Results of Intelligent Tourism Service Design Model

To test the performance of the model's travel interest point recommendation module, this paper selected another five recommendation models for comparative experiments, and the results are shown in Figure 3. The results in the figure show that the performance of all models in the CA data set is lower than their performance in the Gowalla data. In the longitudinal comparison, model BPR has the lowest performance ranking and the lowest accuracy. The accuracy of the model presented in this paper is the highest, and the overall performance is significantly superior to other comparison models. This shows that the interest recommendation module in this paper has a good recommendation effect, which can predict according to customers' interests and improve the corresponding recommendation accuracy based on the correlation between projects.

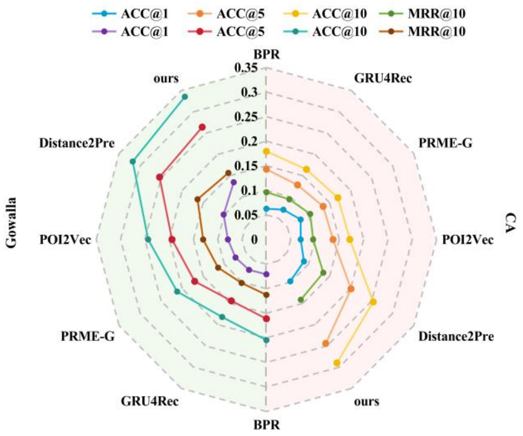

Figure 3: Performance comparison results of six recommended models.

To test the performance of the model's travel route recommendation module, this paper randomly selected tourist attractions in six cities as experimental objects, and selected another four route recommendation models for comparison. The experimental results are shown in Figure 4. The results in the figure show that among the other four models, the NSGA-II model scores relatively high on the recommended routes for tourist attractions in different cities, with scores above 90 for all cities except city A. The results of the route recommendation of the other three models are relatively low, and there is a large gap in the scores of the six cities, that is, the stability performance of the model is poor. The recommended route scores of the six cities in this model are all above 110 points, and the scores among the cities are relatively stable, showing good stability. It can be seen that the travel route recommendation module of this model can recommend better travel routes according to the analysis results of customer behaviour and preference and the actual situation of tourist areas.

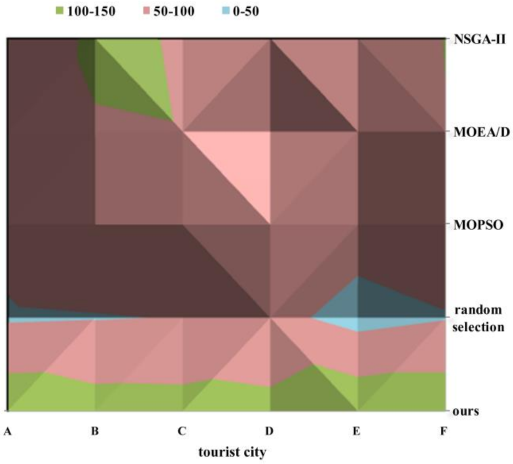

Figure 4: Performance comparison results of five travel route recommendation models.

4.2 Experimental Results of Application of Intelligent Tourism Service Design Model

To test the performance of this model in practical application, this paper selected two groups of customers with similar characteristics and travel behaviour characteristics for comparison experiments. The two groups of customers are recorded as M and N, respectively. They are both family groups with the same number of people, similar ages, and similar economic conditions, and their tourist destinations are city B. Among them, the M family is the control group, whose travel service design is completed traditionally, and the N family is the experimental group, whose travel service design is completed by the model in this paper. Taking full account of the environment and climate of city B, this paper will first analyze the travel behavior of the two groups of families in three aspects: travel mode, accommodation conditions, and catering needs. Figure 5 shows the analysis results of two families' tolerance for walking at different distances. It can be seen from the figure that two families have a higher tolerance for walking within one kilometer. When the walking distance exceeds one kilometer, the tolerance of both families decreases significantly, especially for family N. It can be seen that both groups of families are suitable for self-driving travel in city B.

Figure 6 shows the analysis results of the two families' accommodation conditions. The factors that influence travel behavior analysis include customers' perception of the accommodation environment, surrounding facilities, and accommodation distance. It can be seen from the results that the M family has a general tendency to the accommodation environment, surrounding facilities, and catering service factors but a higher tendency to the distance between accommodation and tourist attractions, indicating that they are more inclined to stay in hotels closer to tourist attractions.

N families also have a general tendency towards accommodation environment factors, with a relatively low tendency towards distance from tourist attractions, but the highest tendency towards catering services around accommodation, so they are more inclined to live in hotels with better catering services.

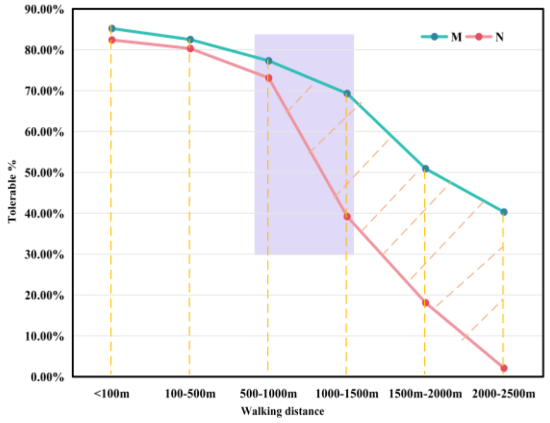

Figure 5: Analysis results of two families' tolerance levels for walking at different distances.

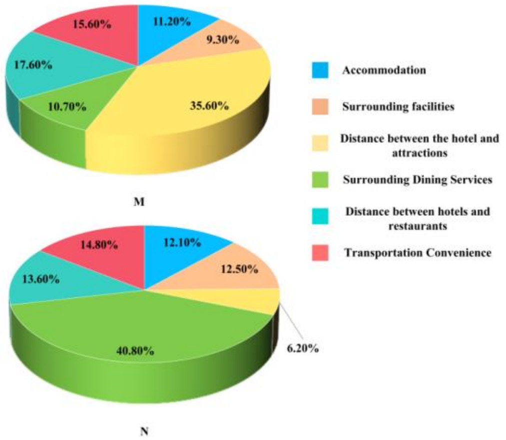

Figure 6: Analysis results of two families' accommodation conditions.

Based on the above customer travel behaviour analysis and customer characteristics, this paper presents the final travel service design results of the two families through the CAD system, including the recommendation of tourist attractions, the recommendation of tourist routes, and the recommendation of hotels, restaurants and other locations, as shown in Figure 7. Figure 7(a) shows the tourism service design results of the M family. The results show that the tourist attractions designed by the traditional tourism service design method according to the preferences and behaviour analysis results of the family are relatively scattered. Among the three recommended accommodation locations, only one hotel has a relatively good location and there are many tourist attractions around. In terms of tourist routes, the design result has the situation of multiple turning back, that is, the situation of circling in a relative area. On the whole, the tourism service design results in a low sense of overall service experience. Figure 7(b) is designed by this model according to the analysis results of N family characteristics and behaviours. In terms of tourist attraction recommendation, the arrangement is compact and compatible with the tourist route, to reduce the phenomenon of route return. In terms of accommodation, the recommended hotels have better catering services around and are closer to the scenic spots, and the overall design results in a better sense of tourism service experience.

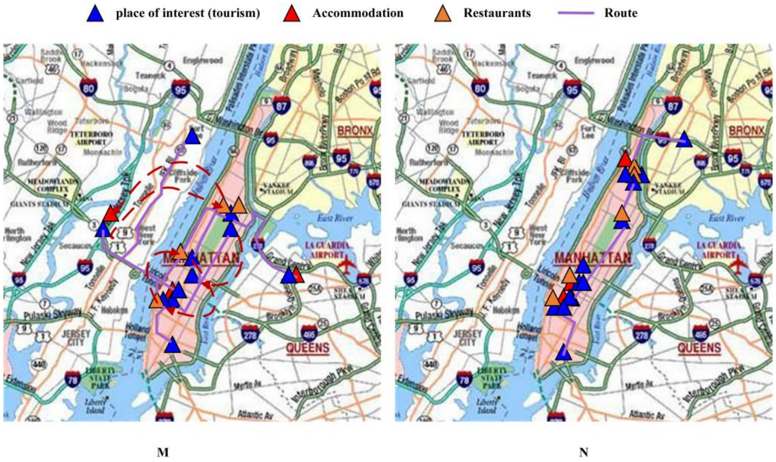

Figure 7: Final travel service design results of the two families.

5 CONCLUSIONS

The transformation of the tourism industry has raised the requirements for tourism service design. At the same time, customers are no longer satisfied with traditional tourism services and tourism forms but are more inclined to travel forms with better service experience. Because of the problems existing in traditional tourism service design, the application of intelligent technology provides a more effective way to improve the quality of tourism service design. To better improve the accuracy of tourism service design, this paper analyzes customer behaviour through the CAD reinforcement learning model and realizes the optimization of tourism service design based on the analysis results. The experimental results show that the proposed model has better recommendation accuracy and stability than other interest tourist destination recommendation models, and can adapt to the actual application environment. At the same time, the model has the best performance in the travel route recommendation score, which can recommend the best travel route according to the preferences, behaviours and characteristics of customers. The results of the applied experiment showed that compared with the control group, The model in this paper can design the optimal travel route for the N family according to its characteristics, travel structure, travel purpose, travel behaviour and other analysis results, and the route can contain the recommended tourist attractions compactly. In addition, the design results of the model in this paper can meet the conditions of N family self-driving tour, and the accommodation selected for the family can take into account both the distance of tourist attractions and catering services, to provide a better service experience for N family and improve tourism quality. However, in the subsequent research, there are still many areas that need to be improved and perfected in this paper. The reinforcement learning model should be further improved to reduce the error rate and improve the analysis speed.

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