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Design and implementation of student job matching system based on personalized recommendation algorithm

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ABSTRACT

In the current job matching of students in higher vocational colleges, the traditional recommendation system often faces some problems, such as inaccurate job information matching, insufficient personalization of recommendation and poor user experience. This paper studies the design and implementation of student job matching system based on personalized recommendation algorithm, aiming at improving students' job matching degree and satisfaction through systematic methods. Firstly, the basic principle of personalized recommendation algorithm, including collaborative filtering and content recommendation algorithm, is discussed, and combined with the employment characteristics of students in higher vocational colleges, the job matching needs are analyzed. It is pointed out that higher vocational students are faced with limited employment opportunities and unequal skill level, so the recommendation system needs to meet the diversification of job information, personalized management of student data and ease of use of the system. When conducting user behavior analysis, it was observed that in a total of 598 user interactions, the average dwell time per user was 3.5 min and the number of page views reached 4.506. This indicates that the user's interest in the content is higher. The statistics of user activity show that the conversion rate is 70.2 %, which shows strong user engagement. There are a total of 523 active events in the system, of which 38 events have significant user interaction frequencies. Finally, this paper provides in-depth theoretical basis and practical guidance for the application of personalized recommendation algorithm in the field of employment matching.

1. Introduction

The student job matching system based on personalized recommendation algorithm aims to provide students with accurate job recommendation by analyzing the matching degree among students' personalized needs, career interests and job requirements [1]. The research motivation of this system stems from the complexity of the current job market and the diversification of individual needs. Different students pay different attention to the employment process. Some students pay more attention to the geographical location of their jobs, while others prefer salary, or the prospect and stability of the industry [2,3]. Traditional employment guidance methods are difficult to fully take into account these complex variables, while the system based on recommendation algorithm can use a large amount of data to accurately analyze the different needs of each student, thus providing a more personalized job matching scheme. The practical significance of this system lies in the fact that it cannot only improve the employment rate of students, but also significantly improve the job matching degree and students' satisfaction [4]. Through data analysis of students' academic qualifications, majors, career interests, personality traits, job expectations and other multi-dimensional information, the recommendation system can screen out job opportunities that meet students' needs according to their personalized characteristics [5,6]. In this way, students can not only find jobs that meet their own interests and abilities faster when they graduate, but also reduce the risk of unemployment after graduation, and at the same time improve their long-term development potential after employment. The key technology of designing and implementing this system lies in the application of personalized recommendation algorithm. The core of recommendation algorithm lies in its ability to mine the best matching degree between individual needs and external resources from a large amount of data [7,8]. At present, collaborative filtering algorithm, content-based recommendation algorithm and hybrid recommendation algorithm are the most commonly used technical methods. In the student job matching system, the collaborative filtering algorithm can speculate the positions that the student may be interested in by analyzing the job-seeking behavior of

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users similar to the student. The content-based recommendation algorithm actively matches the positions that best match students' conditions by analyzing their own background information and career interests. The hybrid recommendation algorithm combines the two to further improve the accuracy and comprehensiveness of recommendation [9,10].

Personalized recommendation systems still face an important challenge, that is, the interpretability of recommendation systems. In the recommendation system, users often want to know the logic and reasons behind the recommendation results, especially in the recommendation of jobs. Students and employers have a higher demand for the transparency of recommendation reasons [11]. In order to solve this problem, introducing knowledge graph into recommendation system has become the mainstream direction of current research. Knowledge graph is a complex heterogeneous network structure, which contains rich semantic information and can provide unique auxiliary information for recommendation systems [12,13]. By constructing a knowledge map related to students' professional interests and job requirements, the system can better understand and express the complex relationship between students and jobs. This can not only effectively solve the problem of data sparsity, but also greatly improve the interpretability of the recommendation system. More and more scholars apply knowledge graphs to the research of recommendation systems [14,15]. Through the knowledge map, the recommendation system can establish a clear connection between students' professional interests, skill requirements and jobs. Compared with traditional recommendation based on historical data, knowledge graph can not only improve the accuracy of recommendation results, but also enable the recommendation system to have explanatory ability and help students understand why a certain position is suitable for them [16,17]. In this way, students can not only obtain recommendation results that are more in line with their own needs, but also have a higher sense of trust in the recommendation results, thus improving the overall use effect of the employment matching system [18,19]. The remainder of this paper is structured as follows: Section 2 introduces the theoretical foundation and algorithm principles, including collaborative filtering and knowledge graph integration. Section 3 details the demand analysis for the job matching system, considering the needs of students, teachers, and employers. Section 4 presents the design and implementation of personalized recommendation algorithms, including system architecture and key technical solutions. Section 5 evaluates the system through experimental analysis, comparing algorithm performance and user feedback. Finally, Section 6 concludes the study and outlines future research directions.

2. Theoretical basis and algorithm technology

2.1. Basic principles and classification of personalized recommendation algorithms

The basic principle of personalized recommendation algorithm can be summarized as finding the best matching relationship between users and items through data mining and machine learning technology. As shown in Eqs. (1) and (2), $S(u_i, u_j)$ represents the similarity between user i and user j, and r_i and r_j are the average scores of users i and j, respectively. u_i represents the interest vector of user i, r_{ik} represents the user's rating of item k, v_k represents the feature vector of item k, and n is the number of items rated by the user. There are many kinds of recommendation algorithms, mainly including collaborative filtering, content-based recommendation and mixed recommendation.

$$u_i = \frac{1}{n}\sum_{k=1}^{n} r_{ik} v_k \tag{1}$$

$$S(u_i, u_j) = \frac{\sum_{k-1}^{n}(r_{ik} - \overline{r_i})(r_{jk} - \overline{r_j})}{\sqrt{\sum_{k-1}^{n}(r_{ik} - \overline{r_i})^2 \sum_{k-1}^{n}(r_{jk} - \overline{r_j})^2}} \tag{2}$$

Collaborative filtering algorithm makes recommendations for target users by analyzing the behavior data of similar users, such as the job information applied by other students with similar career interests. As shown in Eqs. (3) and (4), $N(i)$ is a set of items similar to item i, and $S(i,j)$ is the similarity between items. r_{ui} is the predicted score of user u for item i, and $N(u)$ is the set of users similar to user u. The content-based recommendation algorithm mainly matches students' personal data and resume information, and automatically matches them with the most suitable job requirements. The hybrid recommendation algorithm combines the two to improve the comprehensiveness and accuracy of recommendation.

$$\widehat{r}_{ui} = \overline{r_u} + \frac{\sum_{v \in N(u)} S(u,v)(r_{vi} - \overline{r_v})}{\sum_{v \in N(u)} |S(u,v)|} \tag{3}$$

$$\widehat{r}_{ui} = \frac{\sum_{j \in N(i)} S(i,j) r_{uj}}{\sum_{j \in N(i)} |S(i,j)|} \tag{4}$$

The student employment position matching system based on personalized recommendation algorithm aims to analyze the matching degree among students' personalized needs, career interests and job requirements. As shown in Eqs. (5) and (6), $P(u,j)$ is the recommendation score of user u for job j, x_{uf} and y_{jf} are the feature vectors of users and jobs respectively, and w_f is the feature weight. I_u represents the weighted interest of user u in a domain, f_{uc} is the interest score of user u in domain c, and w_c is the weight of domain. Provide students with more accurate job recommendations, thus improving employment rate and job satisfaction. The research motivation of this system stems from the low efficiency of traditional employment guidance mode in processing large-scale personalized data, which can't accurately help students find suitable job opportunities quickly.

$$I_u = \frac{\sum_{c \in C} w_c f_{uc}}{\sum_{c \in C} w_c} \tag{5}$$

$$P(u,j) = \sum_{f=1}^{m} w_f x_{uf} y_{jf} \tag{6}$$

In the traditional recommendation algorithm, the recommendation results often lack interpretability, and it is difficult for users (students) to understand why the system recommends certain positions. Therefore, the introduction of knowledge graph has brought new breakthroughs to the recommendation system. As shown in Eq. (7), R is the user-post scoring matrix, U and V are the implicit feature matrices of users and posts, and W is the feature weight matrix. Knowledge graph is a complex heterogeneous network structure, which not only contains rich semantic information, but also shows the hidden complex relationship between users and objects. In this study, knowledge graph structure information and collaborative recommendation algorithm are combined in an end-to-end neural network for the first time, which further improves the accuracy of recommendation by capturing the deep correlation between users and positions.

$$R = UWV^T \tag{7}$$

By introducing the knowledge graph into the personalized recommendation system, students can clearly see the reasons and basis for the system to recommend a certain position. For example, the system can display the connection between a student's professional skills and the core requirements of the position through the knowledge graph, as well as the background information of other people who have worked in this position. As shown in Eq. (8), C_u is the trust degree of user u in the recommendation system, and B_k is the weight of item k. It not only improves the interpretability of the recommendation system, but also enhances students' trust and acceptance of the recommendation system. Knowledge graphs can also effectively solve common data sparsity problems in recommendation systems.

$$C_u = \sum_{k=1}^{n} B_k \cdot r_{uk} \tag{8}$$

2.2. Analysis of employment characteristics and job matching needs of students in higher vocational colleges

According to these employment characteristics of higher vocational students, personalized recommendation algorithm provides them with personalized job recommendation services. The personalized recommendation algorithm not only takes into account the basic background information of students, as shown in Eqs. (9) and (10), f is the learning rate, and updates the user interest vector *ui*. *J(o)* is the loss function, and *TH* is the regularization parameter. It also helps students find jobs that are more suitable for their own conditions by analyzing multi-dimensional data such as professional interests, skill levels, and regional preferences. Through the analysis of students' hobbies and career ideals, we recommend jobs that highly match their career interests.

$$J(o) = \frac{1}{2m}\sum_{i=1}^{m}(\widehat{r}_{ui} - r_{ui})^2 + TH\| o\|^2 \tag{9}$$

$$u_i^{new} = u_i^{old} + f \cdot \frac{\partial J}{\partial u_i} \tag{10}$$

As higher vocational students have strong regional employment tendency, the system will choose according to the students' regions, as shown in formula (11), u_f represents the user's behavior characteristics, a_i is the attention weight, and h_i is the behavior feature vector. Recommend jobs that meet regional preferences. This can not only improve the employment success rate of students, but also reduce the employment loss caused by geographical inconsistency. In the design process of job matching model, personalized recommendation algorithm is one of the core technologies.

$$u_f = \sum_{i=1}^{n} a_i h_i \tag{11}$$

By using this algorithm, the system can automatically infer students' potential intentions according to their historical job search records, interest tendencies, skill levels and other information, and generate targeted job recommendations based on this information. As shown in Eq. (12), z_u is the latent intention of the user, and W_x and W_h are the weight matrices of the eigenvectors, respectively. In order to further improve the accuracy of recommendation, this study uses hierarchical attention neural network to reason the path between users and projects. The network infers students' potential career intentions by deeply learning users' historical behavior data.

$$z_u = \sigma(W_x x_u + W_h h_{t-1}) \tag{12}$$

The system can not only make recommendations according to students' explicit needs, but also infer students' potential intentions through implicit data. As shown in Eq. (13), $p(j|u)$ represents the probability that the user u is recommended for the position j. The advantage of this model lies in its ability to process large amounts of complex multi-dimensional information and infer potential employment intentions in user behavior. This can not only improve the accuracy of recommendation, but also reduce the time cost required by students in the process of job hunting.

$$p(j\backslash u) = \frac{\exp(S(u,j))}{\sum_{k=1}^{n}\exp(S(u,k))} \tag{13}$$

3. Demand analysis of student employment matching system

3.1. Basic needs of employment matching of students in higher vocational colleges

The system needs to design and implement advanced recommendation algorithms, including content-based recommendation, collaborative filtering and mixed recommendation technologies. The algorithm also needs to be continuously optimized to cope with the changing market demand and student demand [20,21]. By introducing deep learning and reinforcement learning technologies, the system can mine potential matching information in massive data and improve the accuracy and personalization of recommendation results. The ease of use and friendliness of the system directly affect the user experience and efficiency [22,23]. For students in higher vocational colleges, the system is designed to have a concise and clear user interface, which is convenient for students to quickly find the required functions and operate them. The system is designed to be designed to conform to the user's operating habits and provide clear guidance and help information [24,25]. For example, through intuitive navigation bar, quick search function and friendly prompt information, the operation convenience of the system is improved. At the same time, the system is designed to also support a variety of device access, including PC and mobile, so as to facilitate students to inquire and apply for jobs anytime and anywhere [26,27]. The effectiveness and accuracy of job recommendation are important indicators to measure system performance. Effective recommendation can not only improve students' success rate of job hunting, but also enhance their trust in the system. Fig. 1 illustrates the core algorithm of the personalized recommendation engine. The system is designed to provide students with positions aligning with their professional interests and skill levels via accurate data analysis and recommendation algorithms.

In order to further improve the effect of recommendation system, in recent years, some scholars have proposed a new recommendation algorithm by combining reinforcement learning with knowledge graph. Reinforcement learning can train agents to traverse the knowledge graph and find the optimal recommendation path, thus improving the accuracy, diversity and fairness of recommendation results [28,29]. The knowledge graph provides a rich network of semantic information and relationships. By guiding reinforcement learning agents to conduct effective path search in the graph, more accurate and personalized job recommendations can be achieved. At the same time, this combination can also improve the interpretability of the recommendation algorithm. By visualizing the recommendation path, highlighting the critical path or providing the text description of the path, the system can make users clearly understand the basis of the recommendation results and increase their trust in the system recommendation [30]. Fig. 2 depicts the algorithm diagram for job feature extraction. The system must comprehensively address multiple needs, including the diversification and dynamic update of job information, personalized management and privacy protection of student data, the efficiency and accuracy of recommendation algorithm, the ease of use and friendliness of the system, etc.

3.2. System user analysis: students, teachers and employers

Teachers hope that the system can provide detailed employment data analysis reports, including students' employment trends, changes in job demands, employment satisfaction, etc. These data can help teachers formulate more effective employment guidance strategies. Teachers hope that the system can provide career planning and guidance tools,

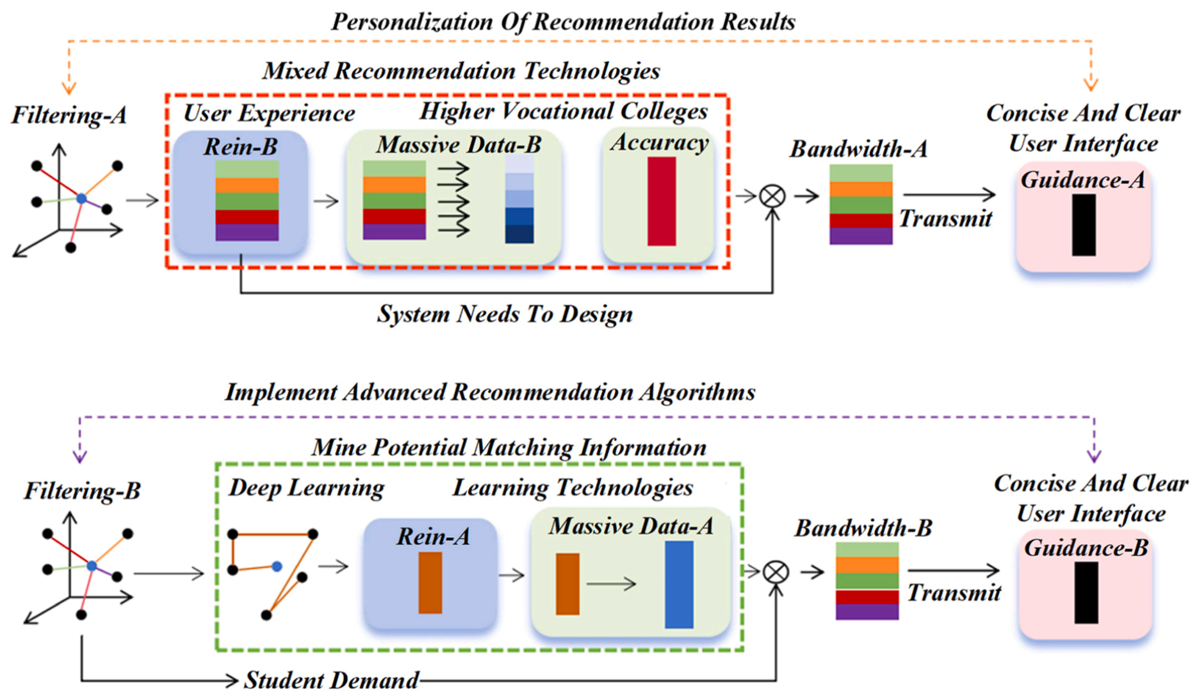

Fig. 1. Core algorithm of personalized recommendation engine.

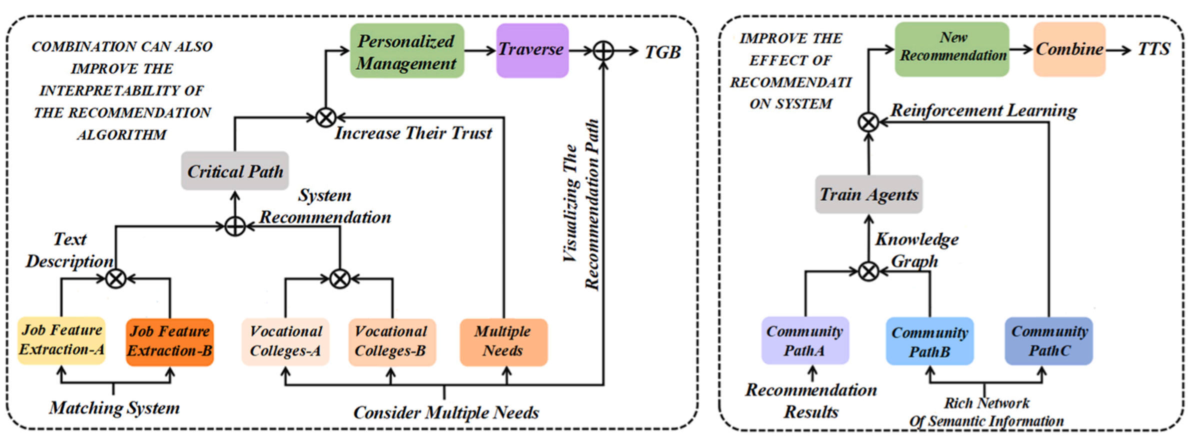

Fig. 2. Post feature extraction algorithm diagram.

such as career interest assessment, career development path suggestions, etc., to help students make career orientation and planning. Teachers hope that the system can provide personalized employment suggestions according to the specific situation of students, so as to improve the employment rate and satisfaction of students. The main demand of employers in the system is to efficiently find graduates who meet the job requirements. They hope that the system can help them accurately screen candidates who meet the recruitment conditions, thus saving recruitment costs and improving recruitment efficiency. Specific requirements include: the employer hopes that the system can provide candidate recommendations that are highly matched with the job requirements, including the candidate's skills, experience, academic background, etc. Employers need to easily publish recruitment information, manage recruitment progress, track candidates' applications, etc. Employers hope that the system can provide feedback data on recruitment effects and help them understand the problems and optimization points in the recruitment process. In the recommendation system, the interpretability of the recommendation model is an important issue. In order to improve the transparency of the system and user trust, it is particularly important to record and explain the recommended path. To achieve this goal, this study proposes a KGRL model that combines reinforcement learning with knowledge graph. Fig. 3 is the evaluation diagram of the job matching dynamic adjustment algorithm. This model combines the decision-making ability of reinforcement learning with the rich semantic information of the knowledge graph to solve the interpretability problem of the recommendation algorithm in the following ways: The KGRL model provides the interpretation of recommendation results by recording the recommendation path. The system can show the specific process and basis of recommendation, so that users can understand why certain positions or candidates are recommended, thus improving their trust in the recommendation results of the system.

The model uses reinforcement learning to train the agent to traverse the knowledge graph and optimize the recommended path. Reinforcement learning adjusts recommendation strategies through continuous decision-making and feedback, while knowledge graphs provide rich semantic information to help the system better understand the complex relationship between user needs and job information. The attention

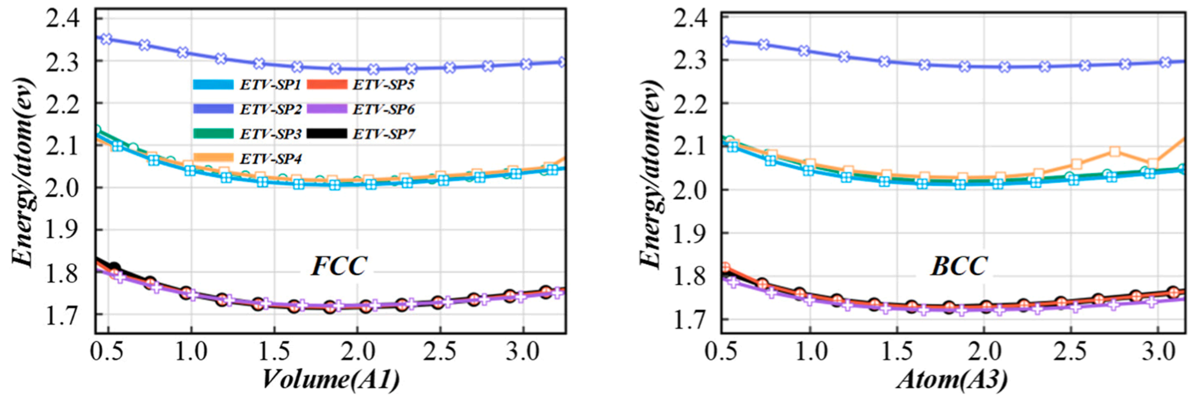

Fig. 3. Evaluation diagram of job matching dynamic adjustment algorithm.

mechanism is employed in the model to capture the long-term semantic relationship between items. This mechanism can better understand the deep relationship between users and positions, thus improving the personalization and accuracy of recommendation results. Although the KGRL model performs well in solving the interpretability problem of the recommendation algorithm, it also has the problem that the accuracy of the recommendation results is not high. Fig. 4 shows the evaluation diagram of the AB test algorithm for personalized recommendation effectiveness. System designers can achieve optimization by continuously monitoring algorithm performance, integrating user feedback, and employing techniques like A/B testing to balance recommendation interpretability and accuracy, ensuring optimal job matching services. The design of job matching system needs to fully consider the needs of different users such as students, teachers and employers. Through the detailed analysis of the functional requirements and usage scenarios of various users, it can provide clear guidance direction for system design.

4. Design and implementation of personalized recommendation algorithm

4.1. Job recommendation method based on collaborative filtering algorithm

User-based collaborative filtering algorithm makes recommendations by analyzing the similarity of users' behaviors and interests. Specifically, this method first finds other users with similar interests and behaviors to the target users, and then recommends the positions that these similar users like to the target users. The core of this method lies in using the behavioral data of user groups to discover potential job points of interest. Collect students' job-seeking behavior data, including browsing history, application records, job clicks, etc., and establish a user behavior database. Calculating the similarity between students and other users can be matched through multi-dimensional information such as users' interest tags and skill backgrounds. According to the job selection of similar users, a personalized job recommendation list for target students is generated. The project-based collaborative filtering algorithm focuses on the characteristics of the job itself, rather than the user. This method makes recommendation by analyzing the similarity between positions. Specifically, the algorithm will find other positions similar to the target position according to the attributes of the position, and recommend these similar positions to users. Fig. 5 is a user behavior analysis and recommendation optimization evaluation diagram, which models the detailed attribute information of the position, including skill requirements, work location, industry type, etc. By calculating the similarity between positions, other positions similar to the target position are found, and a recommendation list is generated. According to the change of market demand and job information, the job similarity calculation model is dynamically updated to keep the timeliness and accuracy of recommendation.

In order to improve the accuracy and interpretability of the recommendation system, the collaborative filtering algorithm needs to be improved. In the process of model training, designing and optimizing the loss function is the key to improve the performance of the algorithm. In this chapter, the training characteristics of different stages are analyzed in detail, and the TransR translation model is used to integrate the map features into the loss function design. The TransR model improves the model's ability to capture complex relationships by mapping entities and relationships into different spaces. The pairwise-based loss function and the regularized loss function are combined to update and optimize the model. The pairwise loss function can help the model better distinguish between related and unrelated positions, while the regularization loss is used to prevent the overfitting of the model and improve

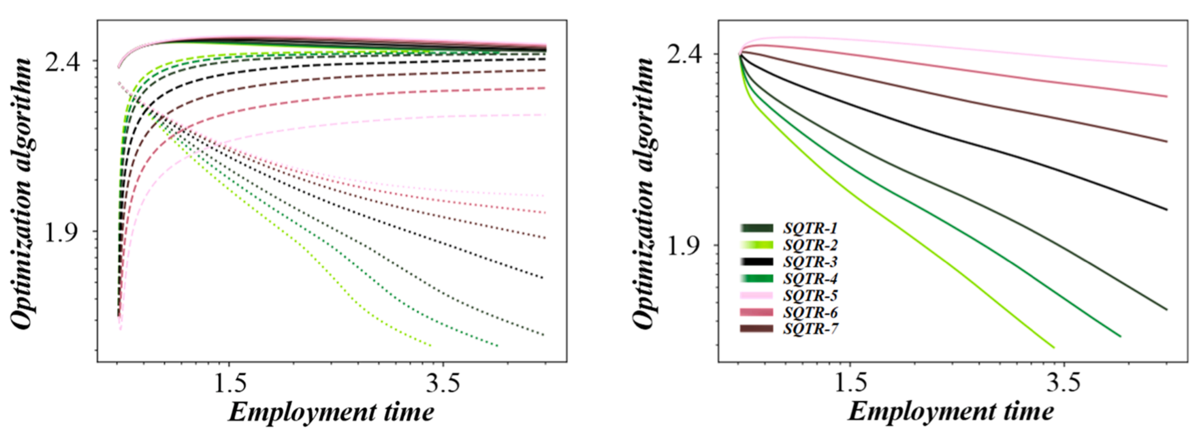

Fig. 4. Personalized recommendation effect AB test algorithm evaluation diagram.

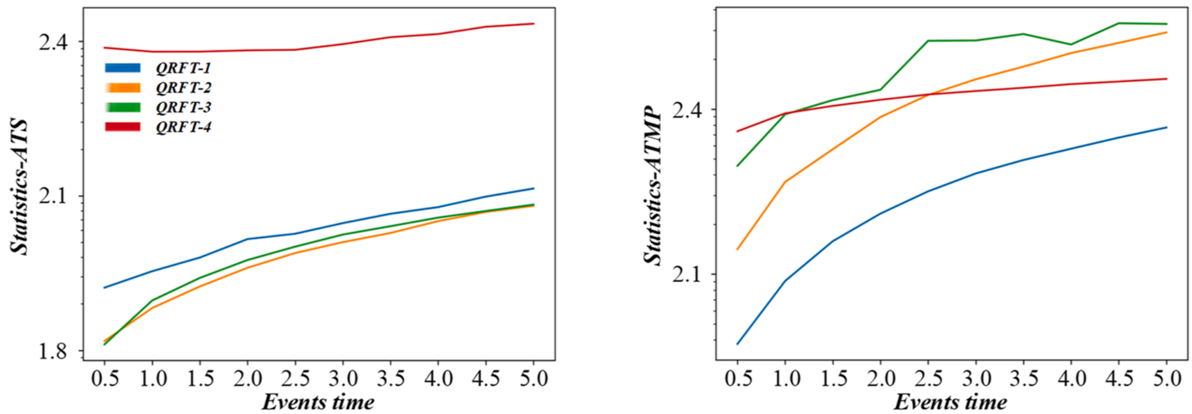

Fig. 5. User behavior analysis and recommendation optimization evaluation diagram.

the generalization ability. Fig. 6 is the evaluation diagram of the accuracy evaluation algorithm of the recommendation system. During the training process of content and content attribute entity nodes, the knowledge graph is used for modeling. By learning the low-dimensional vector representation of entity nodes and their edges, the knowledge graph explicitly captures the relationship between nodes and edges, so as to encode more information in the message propagation process of the model.

This method can improve the interpretability of recommendation results, and make the system provide more transparent recommendation reasons. The dataset utilized in this study comprises 16,998 student profiles and 9197 job postings collected from three vocational colleges and 500 cooperating enterprises. Key features include: Student Attributes: Educational background (diploma type, major, GPA), skills (certifications, programming languages, clinical skills for medical majors), work experience (internships, part-time jobs), and job preferences (location, salary expectations, industry). Job Attributes: Skill requirements (textual descriptions processed via NLP), industry type, work location, salary range, and company size. Table 1 shows the entity statistics of knowledge graph. In the design and implementation of student job matching system based on personalized recommendation algorithm, collaborative filtering algorithm, as an effective recommendation method, needs to be optimized according to the characteristics of higher vocational students. By improving the design of loss function, combining knowledge graph and reinforcement learning, and improving the interpretability of recommendation results, the recommendation accuracy and user experience of the system can be significantly improved.

Table 1
Knowledge graph entity statistics.

Entity type	Description	Quantity
User	User	16,998
Item	Commodity	9197
Feature	Trait	17,168
Brand	Brand	1578
Category	Category	188

4.2. Job matching strategy based on content recommendation algorithm

Content recommendation algorithm is based on the content of job description, and generates personalized recommendation by analyzing and matching content features. First of all, the system needs to collect and sort out students' personal information, including educational background, skills and expertise, work experience, etc. By systematizing these information, the students' personal professional files are constructed. Understanding a student's career interests and career goals is key to referral. Practically, this means the system must collect and analyze data on students' preferences (e.g., industry inclination, skill strengths, long-term career aspirations) to generate recommendations that not only match immediate job requirements but also align with their long-term professional development. This information can help the system further refine the recommendation. Among content recommendation algorithms, text mining and natural language processing (NLP) techniques are crucial. These techniques are used to extract and understand critical information from job descriptions. Use text mining technology to extract key characteristics from job description, such as job title, main responsibilities, necessary skills, job location, etc. Through NLP technology, the text is processed by word segmentation, part-of-speech tagging and entity recognition, and important information related to the post is extracted. Fig. 7 is a real-time feedback adjustment mechanism algorithm evaluation diagram, using semantic analysis technology to understand the deep meaning of job description. For example, through word vector representation or semantic embedding model, the job description is transformed into a form that the computer can understand, so as to accurately capture the core requirements and responsibilities of the job.

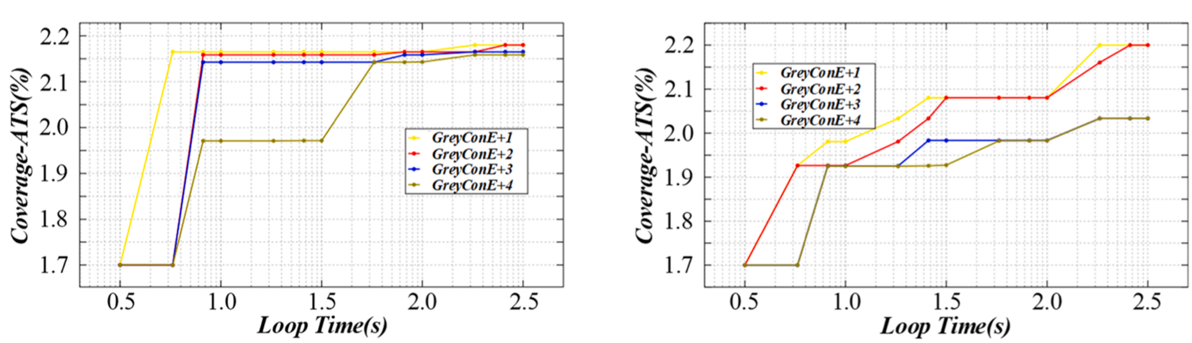

Fig. 6. Evaluation diagram of recommendation system accuracy evaluation algorithm.

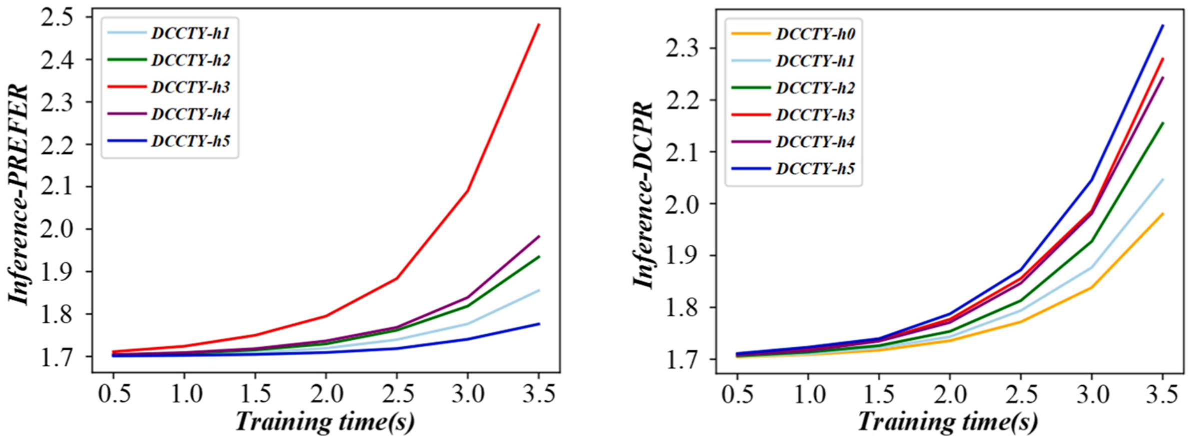

Fig. 7. Algorithm evaluation diagram of real-time feedback adjustment mechanism.

The extracted post characteristics are matched with the student's personal background information. By calculating the similarity between students' backgrounds and job characteristics, a personalized job recommendation list is generated. This process involves similarity calculation, feature weight adjustment and other techniques to ensure the accuracy of recommendation results. Feature extraction method based on graph structure data has gradually become a research hotspot. To enhance system reliability and reduce manufacturing costs, the cooling water structure was simplified through iterative experimental validation. This modification streamlined the pipeline layout while maintaining the same heat dissipation efficiency, as confirmed by thermal performance tests. The simplification process prioritized maintaining critical flow dynamics and temperature control, ensuring no compromise on system functionality or energy efficiency. Fig. 8 is a prediction model evaluation diagram driven by historical employment data. Using nonlinear transformation to process the graph structure data can further improve the ability of feature extraction. Nonlinear transformation abstracts and expresses the features of graph data in a deeper level through complex function mapping, which improves the ability of feature expression.

A feature extraction method based on semi-supervised learning combines the advantages of graph structure data and extracts useful features from graph data through steps such as node embedding representation, neighborhood message aggregation and nonlinear transformation. Our work primarily employs a hybrid framework integrating semi-supervised learning with supervised and unsupervised techniques. Semi-supervised learning is used to leverage limited labeled data and abundant unlabeled data (e.g., job descriptions, student profiles) for feature extraction, while supervised learning refines recommendation accuracy through labeled matching outcomes, and unsupervised learning identifies hidden patterns in user behavior. Through graph embedding technology, the graph structure data is transformed into low-dimensional vector representation, which is convenient for further analysis and processing of graph data. The job matching strategy based on content recommendation algorithm, through comprehensive analysis of personal information, professional interests, skills and past behaviors, uses text mining and natural language processing technology to extract key features from job descriptions, and combines students' backgrounds and interests, can effectively provide personalized job recommendations. Table 2 shows the analysis and comparison of recommendation performance of recommendation algorithms. The application of feature extraction methods based on graph structure data and semi-supervised learning technology further improves the accuracy and practicability of recommendation systems.

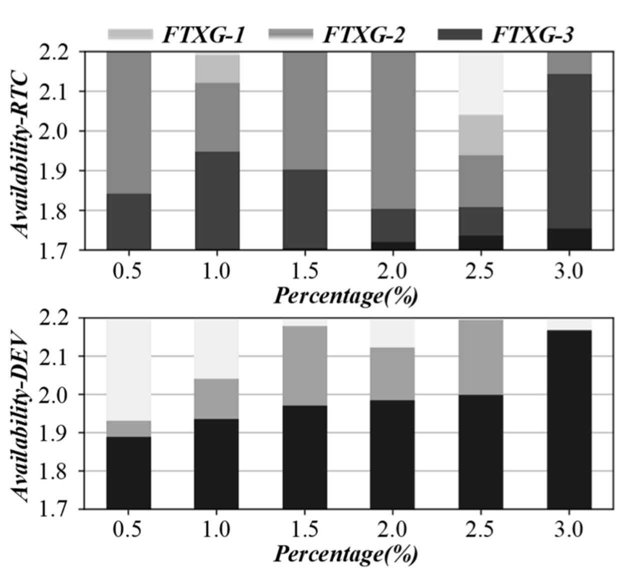

Fig. 8. Evaluation diagram of forecasting model driven by historical employment data.

5. Experimental analysis

The system will use different recommendation algorithms to generate job recommendation results. The main recommendation algorithms include collaborative filtering-based recommendation, content-based recommendation, and hybrid recommendation combining knowledge graph and reinforcement learning. By practical testing of these algorithms, the respective recommendation results can be obtained and comprehensively evaluated. Fig. 9 is the evaluation diagram of the core algorithm for calculating student job matching degree. Comparing the performance of different recommendation algorithms is the core part of experimental analysis. Accuracy is an important index to measure the effectiveness of recommendation algorithms.

Users' satisfaction with recommendation results can be collected through user surveys, questionnaire feedback and actual usage. This

Table 2
Analysis and comparison of recommendation performance of recommendation algorithms.

Portfolio category	NDCG	Recall	HR	Prec.	ETD
[30,4,1]	0.385	0.383	3.46	0.345	1.267
[20,6,1]	0.596	0.465	5.386	0.556	1.252
[20,3,2]	0.442	0.634	3.338	0.345	1.213
[15,8,1]	0.764	0.508	6.333	0.676	1.209
[15,4,2]	0.438	0.405	3.694	0.38	1.22

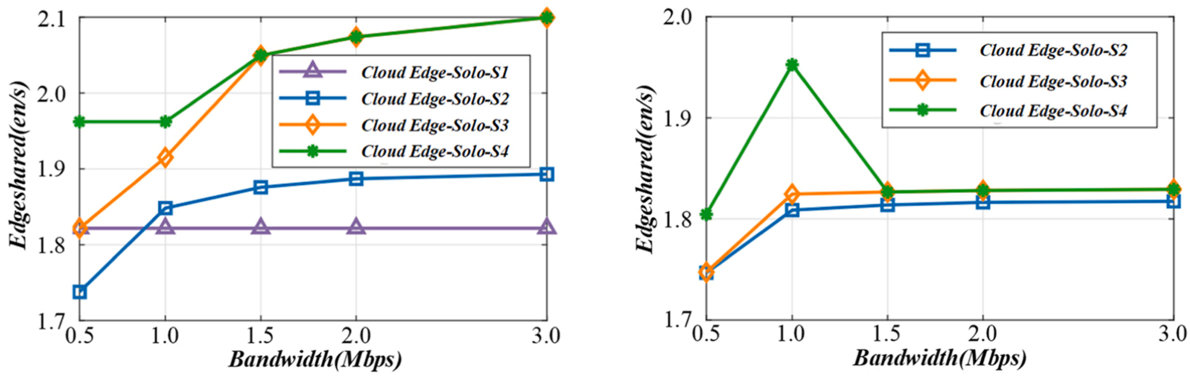

Fig. 9. Evaluation diagram of core algorithm for calculating student job matching degree.

information will help understand the user's acceptance of the recommendation results and the actual experience of using them. In order to better integrate the information, the model performs heterogeneous graph modeling on the multi-behavior interaction data between users and content. Fig. 10 is a personalized recommendation engine evaluation diagram based on interest preferences. This modeling method can make full use of different types of interaction data to capture the complex relationship between users and content. The feature fusion mechanism of complex relationship between user and content side is added to the model.

The RL agent navigates the knowledge graph to find optimal recommendation paths (e.g., student major → related job category → high-demand enterprises), dynamically balancing exploration (discovering new jobs) and exploitation (recommending proven matches), leading to higher recall and precision compared to static CB or CF. Fig. 11 is a job requirement feature extraction and evaluation diagram, which comprehensively evaluates the actual effect of the recommendation algorithm and the overall performance of the system. By comparing the performance of different algorithms in job matching and analyzing the accuracy, efficiency and user satisfaction of recommendation results, we can find the advantages and disadvantages of each algorithm.

Collaborative filtering-based recommendation algorithms perform well when dealing with large-scale user behavior data, but may face data sparsity problems. Content-based recommendation algorithms can accurately extract job characteristics, but there is still room for improvement in the understanding and matching of content. Table 3 is comparative performance analysis of the proposed Knowledge Graph Reinforcement Learning method.

The hybrid recommendation algorithm combining knowledge graph and reinforcement learning has significant advantages in improving the accuracy and interpretability of recommendation results through rich semantic information and complex relationship modeling. Fig. 12 constructs an algorithm evaluation diagram for student ability portraits, but its computational complexity is high and the processing efficiency needs to be further optimized.

6. Conclusion

The student job matching system based on personalized recommendation algorithm significantly improves students' job matching effect and satisfaction by comprehensively applying collaborative filtering, content recommendation algorithm and advanced technologies such as knowledge graph and reinforcement learning.

(1) The theoretical basis of personalized recommendation algorithm includes collaborative filtering and content-based recommendation methods. Collaborative filtering algorithm makes job recommendation through user behavior data and interest similarity, which is divided into two methods: user-based and project-based.
(2) Students in higher vocational colleges are faced with the challenges of limited job information and unequal skill level in the process of employment. Therefore, the system design needs to meet the needs of diversified job information display and personalized data management.
(3) In the performance evaluation of recommendation system, the accuracy of the overall system reached 8.47, while the accuracy of personalized recommendation was slightly higher, 8.4461. In the user feedback, only 0.8 % of users expressed dissatisfaction,

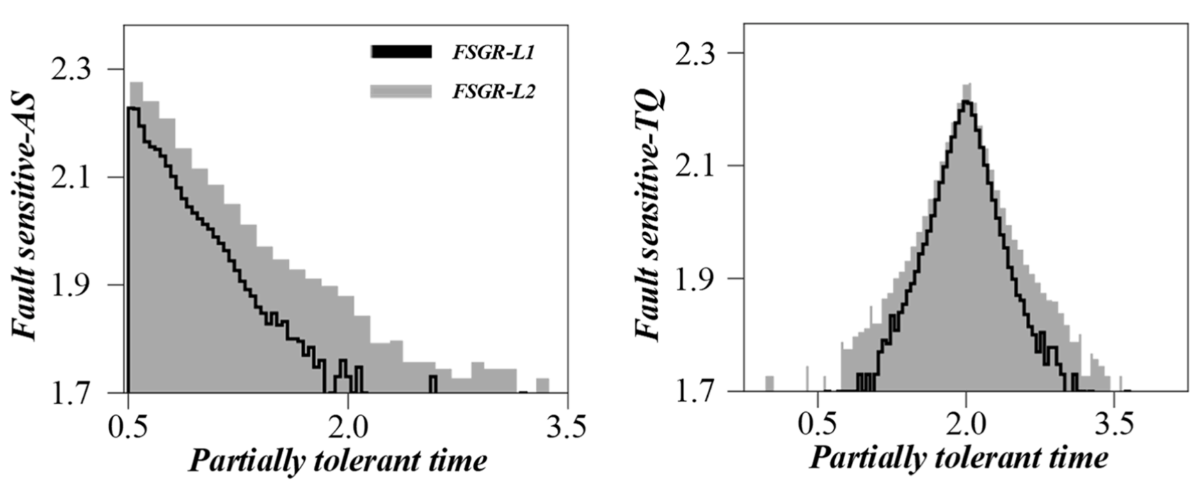

Fig. 10. Evaluation diagram of personalized recommendation engine based on interest preference.

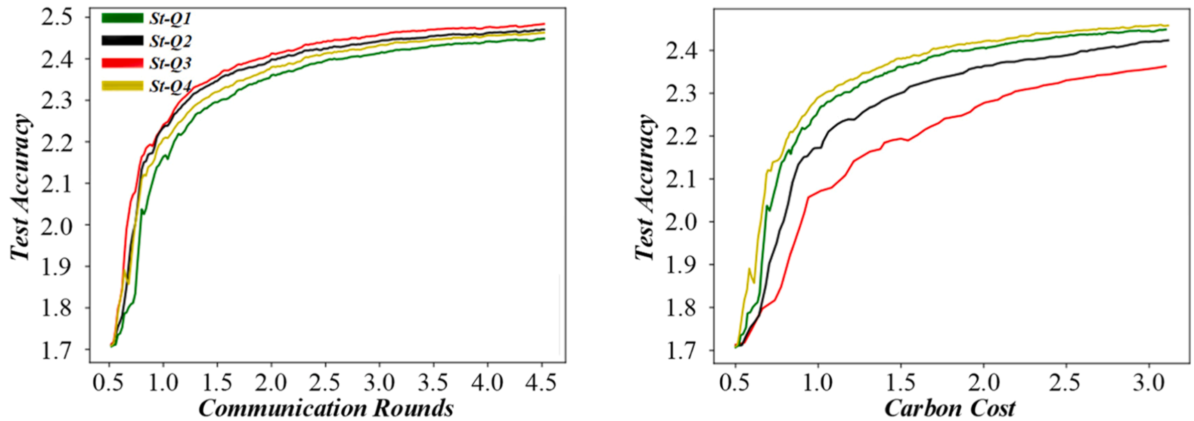

Fig. 11. Job demand feature extraction and evaluation diagram.

Table 3
Comparative performance analysis of the proposed Knowledge Graph Reinforcement Learning method.

Algorithm	NDCG↑	Recall↑	HR@10↑	Precision@5↑	ETD↓ (ms)
CF	0.523	0.412	4.21	0.387	82.5
CB	0.589	0.456	4.89	0.421	75.3
Hybrid (Non-KG)	0.654	0.502	5.33	0.458	91.2
KGRL (Ours)	0.764	0.598	6.87	0.623	68.4

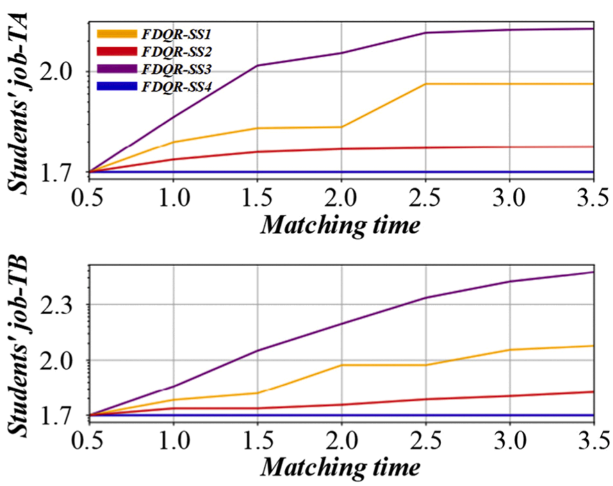

Fig. 12. Evaluation diagram of student ability portrait construction algorithm.

indicating that the satisfaction of the system is high. Considering all things, the average recommendation speed of the system is 6.4 s, while the recommendation accuracy is 0.35 and the coverage rate is 0.772. These data indicate the good performance of the system in recommendation accuracy and efficiency.

CRediT authorship contribution statement

Yu Wang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision.

Declaration of competing interest

The author declares that there is no conflict of interest in this article.

References

[1] Y.X. Cao, P. Liu, Personalized music hybrid recommendation algorithms fusing gene features, Math. Probl. Eng. 2022 (2022) 8.
[2] W. Fang, Y. Sha, M.H. Qi, V.S. Sheng, Movie recommendation algorithm based on ensemble learning, Intell. Automat. Soft. Comput.. 34 (1) (2022) 609–622.
[3] J.J. Gu, Research on precision marketing strategy and personalized recommendation method based on big data drive, Wirel. Commun. Mob. Comput. 2022 (2022) 12.
[4] Y.F. Han, Personalized news recommendation algorithm for event network, Math. Probl. Eng. 2022 (2022) 10.
[5] R. Hou, Music content personalized recommendation system based on a convolutional neural network, Soft. Comput. 28 (2) (2024) 1785–1802.
[6] Y. Huiling, J. Jing, A personalized recommendation technique for travel route based on fuzzy consistent matrix, Mob. Inform. Syst. 2022 (2022) 10.
[7] S.H. Jiang, H.Y. Zhao, Z.Z. Li, A recommendation algorithm based on modified similarity and text content to optimise aggregate diversity, Int. J. Ad Hoc Ubiquit. Comput. 38 (1–3) (2021) 151–157.
[8] W. Jin, User interest modeling and collaborative filtering algorithms application in English personalized learning resource recommendation, Soft. Comput. (2023) 14.
[9] Y.C. Lao, C. Su, B.L. Chen, Y. Li, J. Shi, H.M. Fang, Dynamic personalized recipe recommendations based on facial health recognition, Appl. Sci.-Basel 14 (11) (2024) 14.
[10] W. Li, Z.Y. Li, Q. Luo, Personalized route recommendation for passengers in urban rail transit based on collaborative filtering algorithm, IET Intell. Transp. Syst. (2023) 15.
[11] J.G. Lian, D. Liang, Design and application of multiattribute tourist information recommendation model based on user interest, Wirel. Commun. Mob. Comput. 2022 (2022) 16.
[12] N. Lin, Personalized book intelligent recommendation system design for university libraries based on IBCF algorithm, IEEE Access 12 (2024) 82015–82032.
[13] Q. Lin, S. He, Y. Deng, Method of personalized educational resource recommendation based on LDA and learner's behavior (Publication with Expression of Concern), Int. J. Electr. Eng. Educ. 8 (2021).
[14] D.M. Liu, L.Z. Wang, Y.L. Zhong, Y. Dong, J.L. Kong, Personalized tour itinerary recommendation algorithm based on tourist comprehensive satisfaction, Appl. Sci.-Basel 14 (12) (2024) 32.
[15] R.N. Liu, Simulation of E-learning in English personalized learning recommendation system based on Markov chain algorithm and adaptive learning algorithm, Entertain. Comput. 51 (2024) 7.
[16] Y.F. Liu, J.Y. Li, Z.X. Ren, J. Li, Research on personalized recommendation of higher education resources based on multidimensional association rules, Wirel. Commun. Mob. Comput. 2022 (2022) 11.
[17] Z.C. Liu, L. Wang, X.X. Li, S.B. Pang, A multi-attribute personalized recommendation method for manufacturing service composition with combining collaborative filtering and genetic algorithm, J. Manufact. Syst. 58 (2021) 348–364.
[18] G.P. Lv, Personalized recommendation algorithm of literary works based on annotated corpus, Mob. Inform. Syst. 2022 (2022) 9.
[19] H.L. Pan, Z.J. Zhang, Research on context-awareness mobile tourism E-commerce personalized recommendation model, J. Signal Process. Syst. Signal Image Video Technol. 93 (2–3) (2021) 147–154.
[20] N. Pang, A personalized recommendation algorithm for semantic classification of new book recommendation services for university libraries, Math. Probl. Eng. 2022 (2022) 8.
[21] H.Z. Qu, Y.W. Wang, The application of interactive methods under swarm computing and artificial intelligence in image retrieval and personalized analysis, Visual Comput. 37 (8) (2021) 2331–2340.
[22] X.P. Su, J. He, J. Ren, J.Y. Peng, Personalized Chinese tourism recommendation algorithm based on knowledge graph, Appl. Sci.-Basel 12 (20) (2022) 16.

[23] B. Wang, P.P. Li, Personalized recommendation based on improved speech recognition algorithm in music e-learning course simulation, Entertain. Comput. 52 (2024) 8.
[24] H.G. Wang, W.N. Fu, Personalized learning resource recommendation method based on dynamic collaborative filtering, Mob. Netw. Applic. 26 (1) (2021) 473–487.
[25] F.Q. Zeng, R. Tang, A hybrid music recommendation model based on personalized measurement and game theory, Chin. J. Electron. 32 (6) (2023) 1319–1328.
[26] W. Xi, Research on E-learning interactive English vocabulary recommendation education system based on naive Bayes algorithm, Entertain. Comput. 51 (2024) 9.
[27] F. Zou, D.B. Chen, Q.Z. Xu, Z.Q. Jiang, J.H. Kang, A two-stage personalized recommendation based on multi-objective teaching-learning-based optimization with decomposition, Neurocomputing 452 (2021) 716–727.
[28] Y. Yang, Y.J. Zhao, Personalized sports health recommendation system assisted by Q-learning algorithm, Int. J. Hum. Comput. Interact. (2024) 13.
[29] R.P. Zhang, Personalized course recommendation method based on learner interest mining in educational big data environment, Sci. Program. 2022 (2022) 8.
[30] Y.M. Zhang, The application of E-commerce recommendation system in Smart cities based on big data and cloud computing, Comput. Sci. Inform. Syst. 18 (4) (2021) 1359–1378.