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Research Article

Integration and Sharing Mechanism of Vocational Education Resources from the Perspective of Industry-Education Integration

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Teaching resource platform construction is a systematic project that needs to be constantly enriched and improved in use. The improvement process should always adhere to the principles of school-enterprise cooperation and joint construction and sharing. To solve the problems of weak service content and imperfect sharing mechanism during the construction of the current vocational education teaching resource library, a general framework for the construction of a shared teaching resource platform is designed. To address the problems of low platform resources differentiation and few sharing paths, an intelligent recommendation method based on coupled collaborative filtering and portrait analysis technology is proposed. By introducing attention mechanism and portrait analysis technology into the coupled collaborative filtering model, the platform users and resources are accurately matched to achieve intelligent sharing of vocational education resources.

1. Introduction

The digital teaching resource library is a new type of content produced in the Internet era. It has become an essential element in the construction of double-high vocational colleges to complete the integration of industry and education and do an excellent job in the construction of shared digital teaching resource library [1, 2]. At present, enterprises' participation in the construction of professional teaching resource database belongs to "shallow participation" or even "zero participation". It is necessary to attract enterprises to participate in the construction of resource database for a long time. By keeping the teaching resources updated iteratively and in line with the industry, we can realise the construction and improvement of the professional teaching resource database participated by schools and enterprises [3–5].

The teaching resource library platform has the vital function of promoting active, interactive, and inquiry-based learning for learners. It is an important way to achieve a new teaching model that is open, convenient, and efficient [6]. Teachers create high-quality courses through the resource library platform to achieve rapid uploading and archiving of course resources. Integrating with classroom teaching enriches teaching methods and enhances teaching effects. Professional clusters of vocational colleges and universities can be established through a shared digital teaching resource base with real participation of enterprises. We close school-enterprise cooperation, deepen the integration of production and education, promote teaching reform, improve teaching quality, and thus improve the quality of talent training. We expand the use of the resource library and upgrade it to practitioners of relevant industries throughout the society to enhance social service power and improve professional influence [7, 8].

In the process of integrating industry and education in practice, most vocational colleges and universities have established teaching resource library platforms of a specific scale, relying on their professional and resource advantageous features. However, due to differences in schooling resources and enterprise needs, there are significant differences in the construction strategies and development paths of vocational education teaching resource library platforms. In general, the construction of industry-education integration platform is still in the exploration stage. Problems such as deviation in targeting, weak service content, imperfect sharing mechanism, and insufficient intelligent resource recommendation need to be solved [9]. To solve these problems, literature [10] analysed the contradictions in the construction of existing teaching resource library platforms and sought breakthroughs in institutional mechanisms to solve the problem. In the context of "Internet+", literature [11] established a new model of "O2O" teaching and a sharing mechanism of school-enterprise co-management in an informationized atmosphere, focusing on the objective of building an informationized platform of teaching resources for the integration of industry and education. Literature [12] puts forward relevant suggestions for the implementation of comprehensive applied talent education, hoping to achieve innovation in teaching methods through the construction of a "four-in-one" collaborative platform of industry-university-research-application. Literature [13, 14] are based on the consensus sharing thinking of blockchain to achieve the goal of distributed management and information sharing of production and education integration resources of higher vocational education. Literature [15, 16] constructed a mobile Internet education platform from the perspective of integration of industry and education in response to the problems of low satisfaction in the use of traditional education teaching platforms, poor operational stability, and single form of information resources. Through the organic combination of online teaching and traditional teaching methods, the teaching efficiency and quality of vocational colleges and universities are effectively improved. The literature [17] constructed a personalised learning platform, using intelligent algorithms to achieve the purpose of differentiated education for platform users.

Although the abovementioned methods can effectively enhance the problem of resource utilisation in the construction of the industry-education integration platform, the structure and plans for the sharing mechanism have also been given a certain degree of discussion. However, there are some limitations faced in the construction of the current teaching resource base. The number of existing platform resources is huge but not highly differentiated, and the intelligent recommendation of platform is not sufficiently studied. To solve this problem, the paper proposes an intelligent recommendation method based on improved coupling collaborative filtering and portrait analysis technology, which realises the accurate matching of platform users and resources, and provides personalised resource intelligent recommendation services for each user.

The innovations and contributions of this paper are as follows.

(1) This paper puts forward a shared vocational education teaching resource platform architecture, which improves the shortcomings of weak service content and imperfect sharing mechanism in the construction of the existing platform.

(2) An intelligent recommendation method is proposed to make accurate resource recommendations to platform users by introducing attention mechanism and portrait analysis technology into the coupled collaborative filtering model.

This paper consists of four main parts: the first part is the introduction, the second part is methodology, the third part is result analysis and discussion, and the fourth part is the conclusion.

2. Methodology

In the context of industry-education integration, strengthening the construction of shared professional teaching resource platforms has a very important value. It helps to promote vocational education reform and enables profound changes to the teaching mode as well. On the one hand, promoting the construction of shared professional teaching resource platform is beneficial for the sharing of teaching resources and the significant improvement of teaching quality. Schools and enterprises cooperate to build a shared teaching resource platform. Enterprises can provide corresponding supporting equipment and technical support for higher vocational colleges. This model promotes students to use the platform for autonomous learning and autonomous training. Online tutoring is conducive to improve learning efficiency. This allows students to receive online education alongside face-to-face education, making up for the limitations of face-to-face education. On the other hand, promoting the construction of a shared teaching resources platform is conducive to the sustainable development of vocational education, especially in terms of making it more diversified and systematic and avoiding being too bookish and theoretical. It not only enhances the professional characteristics of teaching resources but also ensures the sharing of enterprises. Through effective cooperation with enterprises, enterprise training can be realised. By building a more systematic, complete, and scientific platform of shared professional teaching resources, vocational institutions are of great value in promoting vocational education teaching reform, improving the quality of education and teaching and facilitating the building of professionalism. This problem needs to be paid great attention to by higher vocational colleges, and practical and effective measures should be taken to vigorously promote the construction of shared professional teaching resource platform.

2.1. Integration of Digital Teaching Resources. Resource integration refers to acquiring and integrating resources through mutual actions based on synergistic goals between schools and enterprises. In short, resource integration is the selection, configuration, and activation of different resources to achieve resource optimisation and overall optimum. The joint efforts of schools and enterprises can fully integrate the forces of all sectors of society to develop a resource platform. Through the orderly integration and connection of high-quality teaching resources of universities and relevant typical cases of industry enterprises, we can ensure the diversity and effectiveness of teaching resources platform resources.

In vocational education, teaching resources in schools focus on consolidating basic theory, mostly theoretical knowledge resources, or theoretical knowledge + practical operation resources. The teaching resources of enterprises are mostly applicable cases and work videos of enterprises. In industry-education integration and collaborative education, the teaching based on theoretical knowledge resources and integrating enterprise practical resources can better guide talent training. Therefore, the construction of the teaching resource platform should meet the needs of teachers teaching, students learning, enterprise employees training, and social personnel self-learning to maximise the learning needs of different users and the radiation of resources. Teachers or enterprise experts can adjust the teaching content in real time according to professional development. By updating the teaching mode, we can realise the normalisation of teaching reform and ensure the timeliness of teaching resource platform resources. Figure 1 shows the platform construction objectives. Figure 1 is the construction target of the platform.

To achieve the basic objectives of the construction of four platforms (teacher teaching, student learning, employee training, and social self-study), we should firmly grasp the core of the application and construction of high-quality teaching resources. Encourage enterprises and society to participate in the construction of resource platform. Relying on the big data platform, we should build a high-level professional teaching resource platform with Chinese characteristics, improve the development ability of teaching resources, and continuously deepen the teaching reform. Figure 2 shows the general idea of platform construction. The platform resources should include both teaching resources for professional teachers and learning resources for students of different majors at different learning stages. After the successful construction of the resource platform, the teaching resources can be gradually integrated and extended to other higher vocational colleges, industrial enterprises, and social training institutions to realise multi-party sharing in a complete sense.

The professional teaching resources platform is divided into four sections: basic teaching resources, industry case integration, application support, and management services. The primary teaching resources platform (theoretical teaching) refers to the teaching resources of professional courses, which should focus on professions, positions, courses, and materials and integrate the theoretical contents of vocational skills examinations. The industry case integration platform (practical teaching) refers to the connection between enterprise resources and teaching resources, which should focus on professions, positions, skills, and materials and integrate the practical contents of vocational skills examinations. The application system support (Internet) platform should take big data. The application system support (Internet) platform should be based on big data and cloud computing as the core, integrating massive high-quality resources, mainly with modules for intelligent lesson preparation, school-enterprise collaborative teaching, skills assessment, teaching management and school-enterprise talent sharing. The management platform includes cluster management modules for school resources, enterprise resources, account authentication, business processes and system interfaces. Figure 3 shows the construction of the teaching resources platform. Through an intelligent cloud-based information management platform, a centralised and unified resource management mode is adopted to provide comprehensive services for the majority of institutions, teachers, students, and enterprises.

2.2. Intelligent Recommendation of Teaching Resources Based on Portrait Analysis. There is an explosion of information resources available for users to choose from in shared teaching resource platforms, including vocational education-related courseware, microlessons, catechisms, publicly available online information resources, and quality resources integrated by major professional database providers. It is elementary for users to get lost in the information selection process. Artificial intelligence technology based on portrait analysis can empower the teaching resource platform with accurate recommendations, provide personalised resource recommendation services for platform users, and improve the efficiency of vocational education teaching.

To make this promise a reality, this paper adopts a portrait analysis technology based on the linkage of user portrait and resource portrait, which provides a realistic possibility for implementing accurate and intelligent recommendation for teaching resource platform. User portrait is based on user data to build a user interest portrait model that truly reflects the characteristics of users, and through the description and analysis of user interests, to achieve the dynamic capture and accurate prediction of user information needs [18]. Resource portrait is a resource aggregation model that is structured, identified, correlated, and can provide visualisation. The model is based on objective resources and constructed by using knowledge map. Through the in-depth disclosure of resource characteristics and associations from different knowledge granularity levels, the automatic reasoning of knowledge base and intelligent recommendation of knowledge products are realised. Reference [19]. Figure 4 shows the flow of intelligent recommendation model.

2.2.1. User Profile of the Teaching Resource Platform. A user profile is the labelling of user information, with tags representing the user's interests and tag weights indicating the user's preferences. Therefore, before building the portrait, a fine-grained and multidimensional labelling system needs to be established to portray the essential content of user behavior and preference in a comprehensive and multilevel manner. The creation of user portraits of teaching resource platforms can be divided into five stages: user data acquisition, user data preprocessing, user data mining, user label extraction, and user data visualisation (as shown in Figure 5). In addition, to strengthen the review and

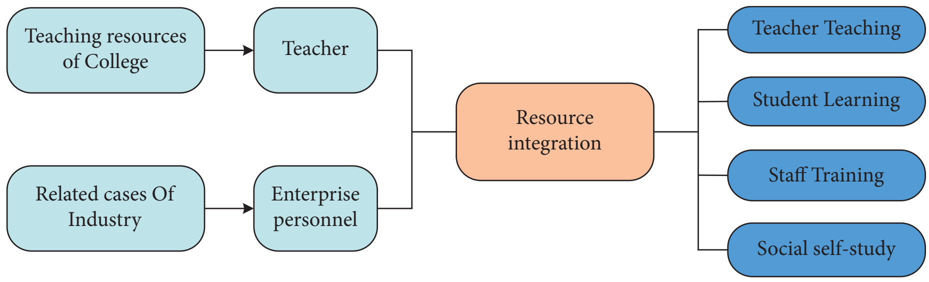

Figure 1: Objectives for the construction of a shared teaching resource platform.

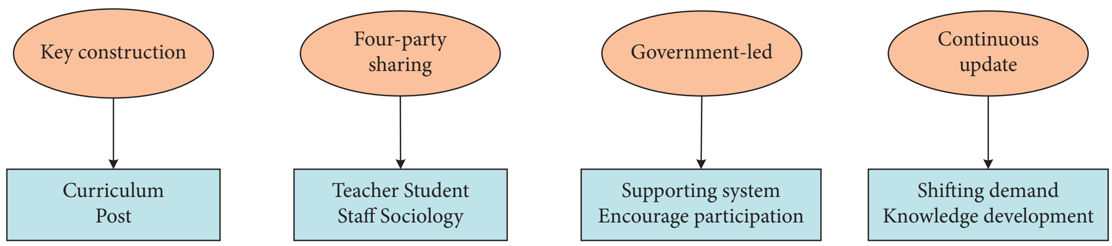

Figure 2: General idea of shared teaching resource platform construction.

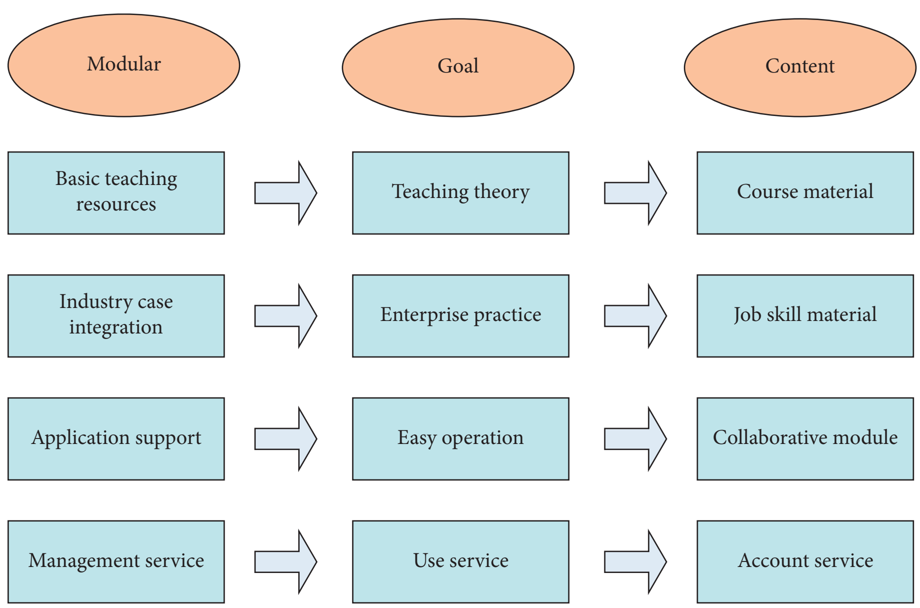

Figure 3: Teaching resource platform construction architecture.

management of user privacy issues and fully protect user data security, user privacy protection must be integrated into the whole process of user profile creation.

(1) User profile tag creation. The acquisition of user data is the original basis for the creation of user portraits. In the stage of user data acquisition, the identity attribute data such as name, major, grade, position, and title of users are obtained from the university information portal system first. Second, the user's knowledge preference data are collected through the user's independent submission and survey feedback. Then, through web crawlers and log acquisition, full flow data collection is carried out for user knowledge interaction behaviour data such as retrieval, browsing, and evaluation of users in the teaching resource platform. Finally, using relevant database construction tools, the abovementioned data are classified and stored to form the initial user database file.

User data preprocessing is a necessary preparation for data mining. In the user data preprocessing phase, the first step is to format and extract multisource heterogeneous data such as user's identity attribute data, knowledge preference data and knowledge interaction behaviour data from the initial user database file, standardise the data format, and realize data conversion for subsequent unification operations.

User data mining is a prerequisite for tag extraction. In the user data mining stage, the first step is to obtain a collection of categorised data from the preprocessed user

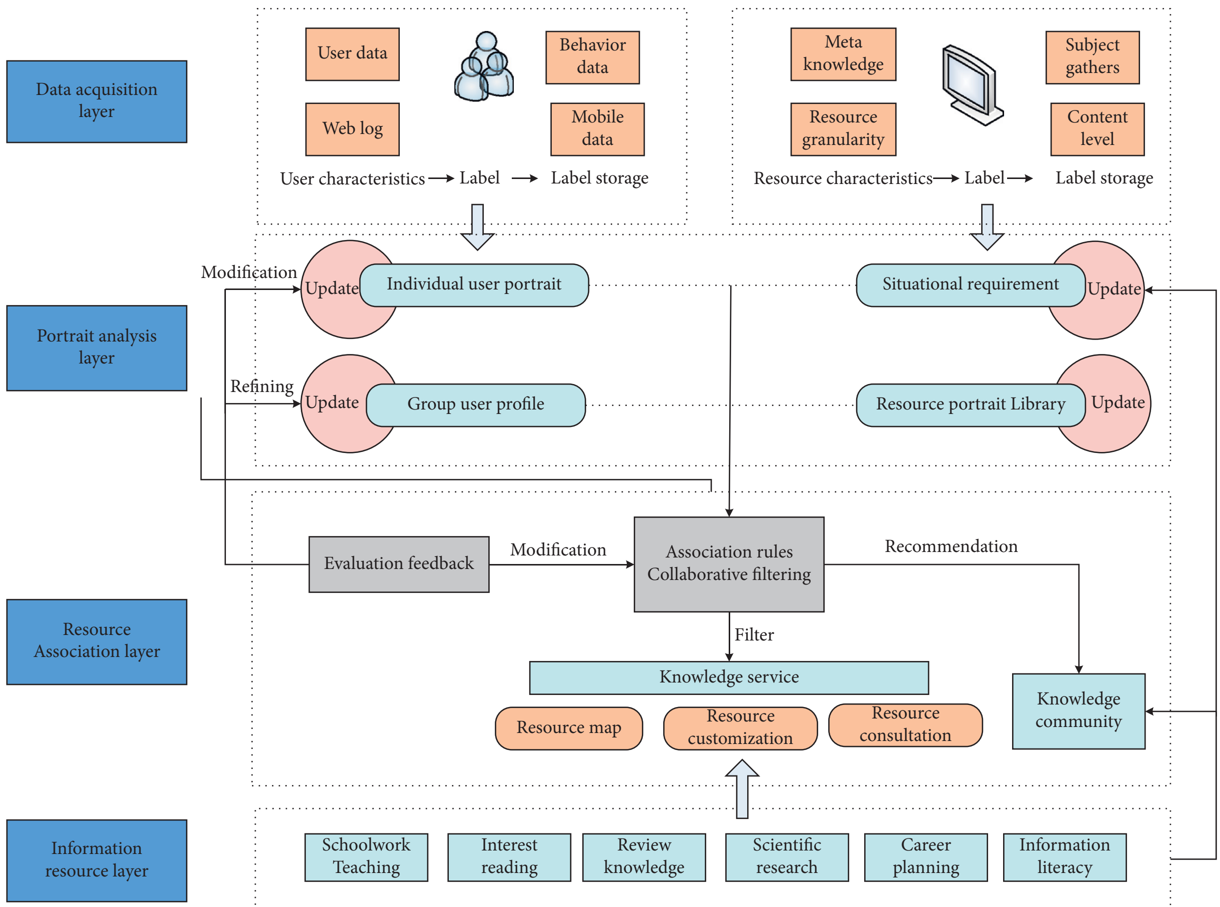

Figure 4: Intelligent recommendation of the teaching resource platform.

database files through data classification and to carry out mining by means of algorithms such as data clustering and semantic analysis, in order to roughly summarise and refine the linguistic expressions of user knowledge demand characteristics. At the same time, because the influence intensity of different factors represented by different data on users' knowledge needs and habits is different, it is necessary to calculate and weight the influence intensity through scientific ways. By giving different data corresponding weight values, the weight values of different labels in the user portrait label system are as appropriate and practical as possible.

The extraction of user tags is the key to the creation of a user profile. In the user label extraction stage, first, the rough extraction results of the data mining layer are further semanticised and refined, and at the same time, manual intervention is used to make appropriate adjustments to the accuracy of label descriptions according to actual needs, so that the user's knowledge demand characteristics can be comprehensively and efficiently portrayed. Second, on the basis of forming the label expression, the feature dimensions to which the label belongs are discriminated and classified through machine learning. Finally, the user profile tagging system is established from four feature dimensions: identity attributes, demand areas, demand preferences, and demand levels.

In the stage of user data visualisation, the characteristics of users' knowledge needs are visualised through visual statistical tools. Finally, the user portrait database is formed by creating the user portrait of the teaching resource platform.

(2) Tag weights and user similarity. TF-IDF algorithm calculates its corresponding weight when extracting keywords, which is used to represent the importance of keywords in the text. To eliminate the influence of nonfeature words on the text topic, only the required nominal words are retained, and the synonym dictionary is used to remove the repetition. The feature words are clustered by K-means, which improve the similarity of user features. The feature words with the highest frequency are selected to represent their feature groups and serve as user feature labels. After determining the user label, the label weight needs to be set. In this paper, the label weight of the user is set as the product of time decay, the behavior type weight, number of behaviors, and the weight obtained from TF-IDF.

Finally, the feature words with the highest ranking weights are selected as the user's feature labels, and the user similarity is obtained by calculating the similarity of the feature labels. The cosine angle method is chosen to calculate the user similarity.

$$\mathrm{Sim}(a, b) = \frac{|N(m) \cap N(n)|}{\sqrt{|N(m)\|N(n)|}}, \tag{1}$$

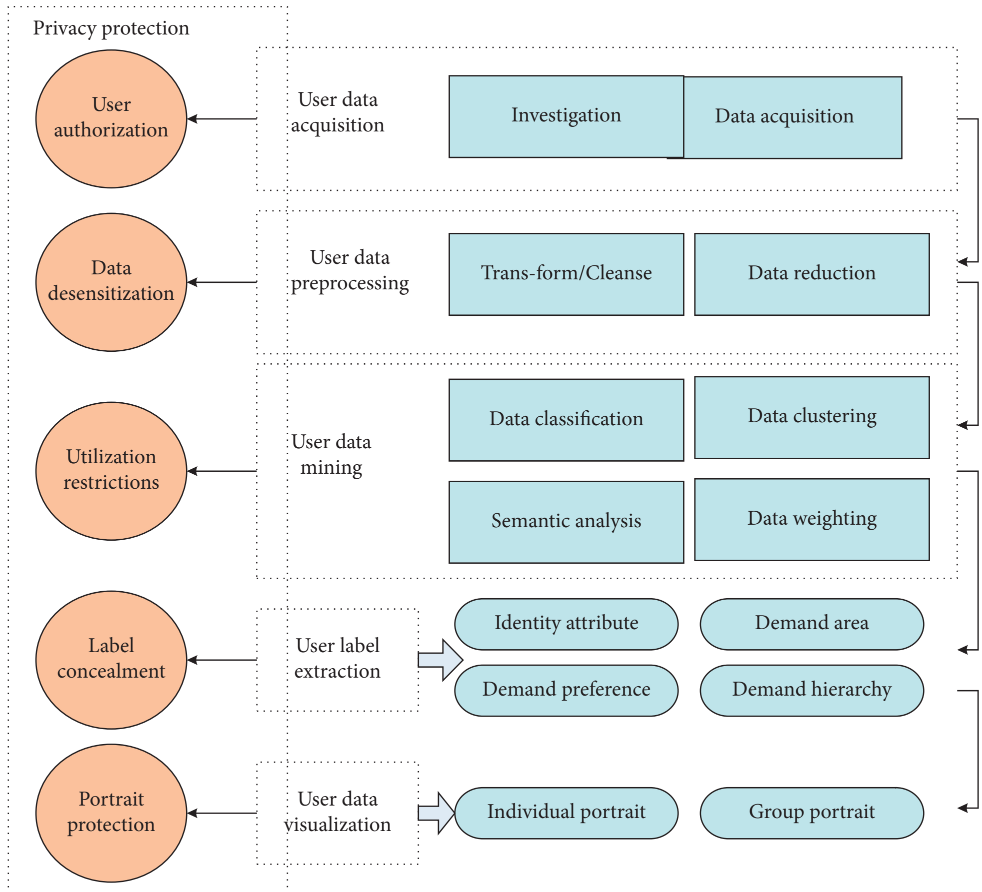

Figure 5: User profile creation process.

where $N(m)$ and $N(n)$ are the sets of labels for users a and b, respectively.

2.2.2. Resource Portrait of the Teaching Resource Platform. The resource portrait of the teaching resource platform is a collection of images that reveal the characteristics and associations of the platform resources. It is a powerful tool for knowledge discovery. However, in terms of providing accurate and real-time knowledge services for a single knowledge problem, it is still necessary to go as far as possible into the smaller granularity knowledge elements and knowledge element sets in the resource content on the basis of coarse-grained portraits. By drawing multi-granularity resource portraits, we can establish a more diversified and accurate mapping relationship between users' knowledge demand and knowledge service supply. The creation of resource portraits on the teaching resource platform can be divided into four stages: resource data processing, resource data revealing, resource data aggregation, and resource data visualization (as shown in Figure 6).

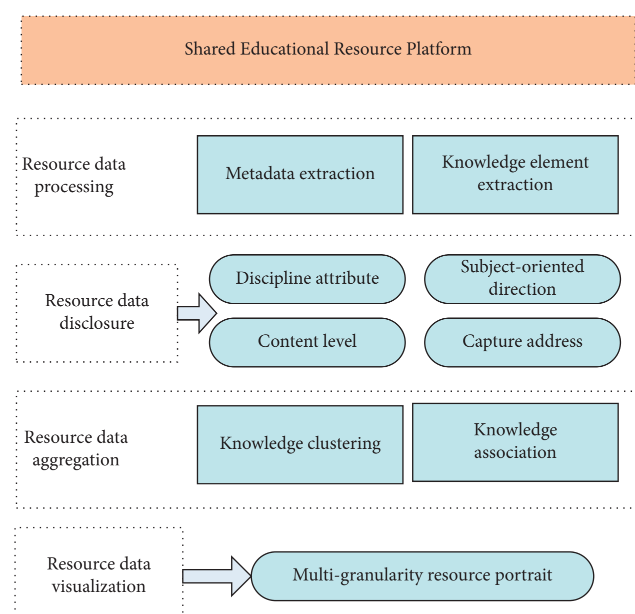

Figure 6: Resource portrait creation process.

(3) Resource portrait creation. The resource data processing phase enables the structuring of knowledge resources. In the resource data processing stage, there are two substages: coarse-grained level structuring based on metadata and fine-grained level structuring based on semantics. For example, for image-based resources, the first substage is: structuring and extracting metadata information such as image title, time, and file type. The second substage is analysing the domain and relevance characteristics of the processed image

resources, constructing a suitable image semantic description model, generating natural language descriptions based on image resources through machine learning, topic models, etc., and extracting knowledge elements and their collections from them, so as to obtain content descriptions of image-based resources.

The resource data disclosure stage realises the identification of knowledge resources. In the resource data disclosure stage, based on the results of resource data processing in the previous stage, multimodal resources such as text, audio, and video with complete work significance are labeled for identification from four characteristic dimensions: subject attribute, subject bias, content level, and acquisition address. The discipline attribute and subject bias dimension form a corresponding relationship with the identity attribute, demand field, and demand preference in the user tag. The former points to the discipline and specialty to which the resource belongs, and the latter points to the subject field to which the resource belongs. The content level dimension forms a corresponding relationship with the demand level in the user tag, pointing to the level depth to which the resource belongs. The access address dimension points to the access channel of the complete resource.

The resource data aggregation stage realises the association of distributed knowledge resources. In the resource data aggregation stage, there are two substages of correlation at the coarse-grained level based on resource labels and at the fine-grained level based on the semantic connotation of knowledge elements, so as to achieve high aggregation and strong correlation between documents and documents and between knowledge elements and knowledge elements. The first substage is able to achieve coarse-grained level association of resources by calculating the similarity of resource labels and establishing strong association between resources with high label similarity. The second substage constructs resource ontology models for each modality and domain by defining core classes and hierarchies, attributes and relationships, rules and reasoning, sensing and mining the external characteristics and intrinsic logical connections between different knowledge elements and their collections in resources, and aggregating the relatively closely connected nodes in each knowledge element and its collection, so as to realize the association of resources at the fine-grained level.

The resource data visualization stage creates resource portraits based on the characteristics of the domain to which the knowledge resources belong, the topics they fit and the tags they have, forming a multigrained resource portrait database. I In the stage of resource data visualisation, visual processing tools and technologies are usually used to make visual interactive files such as knowledge map and keyword cloud. In the form of dynamic and static graph structure, the identified and associated resource content is expressed concretely to form a resource portrait database to realise subsequent resource matching and knowledge service. The multigranularity resource portrait database with rich content and multiple levels has also become the basic support for the realisation of knowledge products such as knowledge map, knowledge report, knowledge customisation, and knowledge consultation.

(4) Resource scoring based on association rules. Association rules are an important technique studied in the field of data mining [20], which can mine the association relationships between sets of items from different categories. Traditional association rule mining finds the set of strong association rules that satisfy the minimum support and confidence level by calculating the support and confidence level of the item set and uses this to help users predict the items they may like based on the items they have already purchased.

In the recommendation problem, the set of all items viewed by each user can be treated as a thing T. Each thing T is a subset of the item set I, and the set of things viewed by all m users constitutes a database D. In this paper, we use the database D to mine the degree of association between items using strong association rules.

Support reflects the probability that one or more item sets appear in database D at the same time. The support degree of item set A and item set B can be expressed as $P\ (A \cup B)$. Confidence reflects the degree of association between two item sets, and the support of item set A to item set B can be expressed as $P\ (B|A)$, which is the probability that item set A occurs while item set B also occurs. The purpose of association rule mining is to find the sets that satisfy the strong association rules to guide the decision of the resource platform.

In this paper, association rules are used to mine first-order and second-order frequent item sets respectively. Taking the confidence of the second-order frequent item set as the weight, the weighted average is carried out with the score value of the user's selected items to predict the value of some non-rated items, improving the sparsity of the user's score data. The calculation method of predicted score value is as follows.

$$P_{ai} = \frac{\sum_{j \in I_a} q_{ij} * R_{aj}}{\sum_{j \in I_a} q_{ij}}, \tag{2}$$

where p_{ai} denotes the predicted rating of item i *by user* a, q_{ij} denotes the support of item j for item i, I_a denotes the set of items rated by user a, and R_{aj} is the rating of item j *by* user a.

2.2.3. Intelligent Recommendation of Teaching Resources. The core of the intelligent recommendation of resources on the teaching resource platform lies in the accurate matching of user demand and resource supply. Therefore, it is not enough to analyse the creation process of user portrait and resource portrait. Still, it is urgent to build further a resource recommendation model for the accurate and intelligent sharing of resources with the platform.

(1) Improved coupled collaborative filtering models. Currently, the most widely used recommendation system in various fields is the collaborative filtering recommendation algorithm. Collaborative filtering is a popular way of implementing recommendation systems, which filters items by user behaviour between people and items to achieve the purpose of recommendation. In response to the traditional collaborative filtering model does not mine and analyse the

different explicit attributes of the user and the item's attention level, and it is difficult to obtain and easy to ignore the user's own interest preference characteristics, a coupled collaborative filtering model based on portrait analysis and attention mechanism is proposed, as shown in Figure 7.

This paper comprehensively considers the explicit and implicit factors. In the explicit feedback network model, attention mechanism is introduced to optimise the effect of feature learning. To extract explicit associations and features between users and items, the relevant attribute inputs of users and items are represented by a and i, while the rating behaviour of users on items will form a user-item matrix R, whose element $r_{m,n}$ represents the rating of the mth user on the nth item. The information relating the user to the item can express the user's explicit preference for the item. To extract the difference of each attribute on user and item preferences, this paper extracts the influence of each attribute by introducing an attention mechanism. The attention weights $H_a and\ H_i$ for user a and item i are as follows:

$$\begin{cases} H_a = f\left(W_a v_a + b_a\right) \\ H_i = f\left(W_i v_i + b_i\right) \end{cases}, \tag{3}$$

where v_a and v_i are the information vectors of user a and item i, *respectively*, and W_a, W_i and b_a, b_i are the weights and bias values of the corresponding neurons in the attention layer, respectively.

The attention weights are then multiplied directly with the vector transmitted by the embedding layer by the dot product of the corresponding elements.

$$\begin{cases} H_{a,\text{out}} = A_a \cdot v_a \\ H_{i,\text{out}} = A_i \cdot v_i \end{cases}, \tag{4}$$

where $H_{a,out}$ and $H_{i,out}$ are the outputs of the user information vector and the project information vector through the attention layer, respectively. To calculate the coupling between the user and the project, $H_{a,out}$ and $H_{i,out}$ are converted into a coupling information matrix R_c by a given coupling function G_θ, which is used to avoid the numerical explosion generated by the coupling process. The elements in R_c are as follows:

$$g_{k,l} = \frac{1}{\sqrt{\left|H_{a,\text{out},k} H_{i,\text{out},l}\right| + 1}}, \tag{5}$$

where $g_{k,l}$ denotes the degree of coupling between the kth element $H_{a,out,\ k}$ in the corresponding attention layer user vector and the lth element $H_{i,out,\ l}$ in the item vector. To avoid numerical explosion caused by excessive multiplication of elements and inhibit the learning of small numerical elements, the coupling relationship is limited to the interval of (0, 1).

In this paper, the coupling information matrix R_c is passed through a convolutional layer to extract its features for deeper networks to learn the features of the coupling relationship.

$$x_{conv} = \text{conv}\left(W_{conv} R_c + b_{conv}\right), \tag{6}$$

where W_{conv} and b_{conv} are the weights and bias values of the neurons in the convolutional layer, respectively. *conv* is the convolution operation. x_{conv} is the output of the convolutional layer, i.e. the desired coupling information features. After the user and item information data have been passed through the embedding, attention, fusion, and convolution layers, the explicit coupling relationships and features can be well learned.

To achieve better recommendation results, the implicit feedback technology is introduced into the model. First, the input information is embedded into a new feature space, with user information and item information encoded as o_a and o_i, respectively, and the embedded vectors as r_a and r_i, respectively. Then, the implicit correlations of users and items are mapped into the same feature space as follows:

$$r = r_a \otimes r_i = \left(r_{a1} r_{i1}, r_{a2} r_{i2}, \cdots, r_{ak} r_{ik}\right), \tag{7}$$

where $\otimes$ is the element-by-element multiplication operation and r_{ak} and r_{ik} are the kth elements of the embedding vectors r_a and r_i, respectively. The nonlinear elements are then introduced into the multilayer perceptron vector model and the implied relationship between the user and the item is learned in depth as follows.

$$\begin{cases} Z_1 = ReLU\left(W_1^{\mathrm{T}} r + b_1\right) \\ Z_2 = ReLU\left(W_2^{\mathrm{T}} r + b_2\right) \\ \vdots \\ Z_L = ReLU\left(W_L^{\mathrm{T}} r + b_L\right) \end{cases} \tag{8}$$

where W_n and b_n are the weights and bias values of the nth layer perceptron, respectively. Z_n is the output of the nth layer perceptron, i.e., the implicit relationship and characteristics of the user and the item.

Finally, the explicit feature H_{conv} and the implicit feature Z_L are spliced into a coupling vector c of users, items through a splicing operation in order to be fed into the fully connected network for learning. Regression prediction is then performed through the fully connected network to obtain the final result of

$$y_1 = f\left(W^{\mathrm{T}} c + b\right), \tag{9}$$

where W and b are the weights and bias values of the fully connected layer neurons, respectively. $f(\cdot)$ is the activation function of the fully connected layer, and the Sigmoid function is usually taken as the activation function to map the output into the (0, 1) interval.

(1) Personalised recommendation models. The personalised recommendation model is based on portrait analysis and collaborative filtering uses portrait analysis and improved collaborative filtering techniques to improve the accuracy of the model's recommendation results. The model first uses association rules to match the feature vectors of user portraits and resource portraits and predicts the rating value y *of* user a for item i from the ratings of user a's nearest neighbours p_{ai}

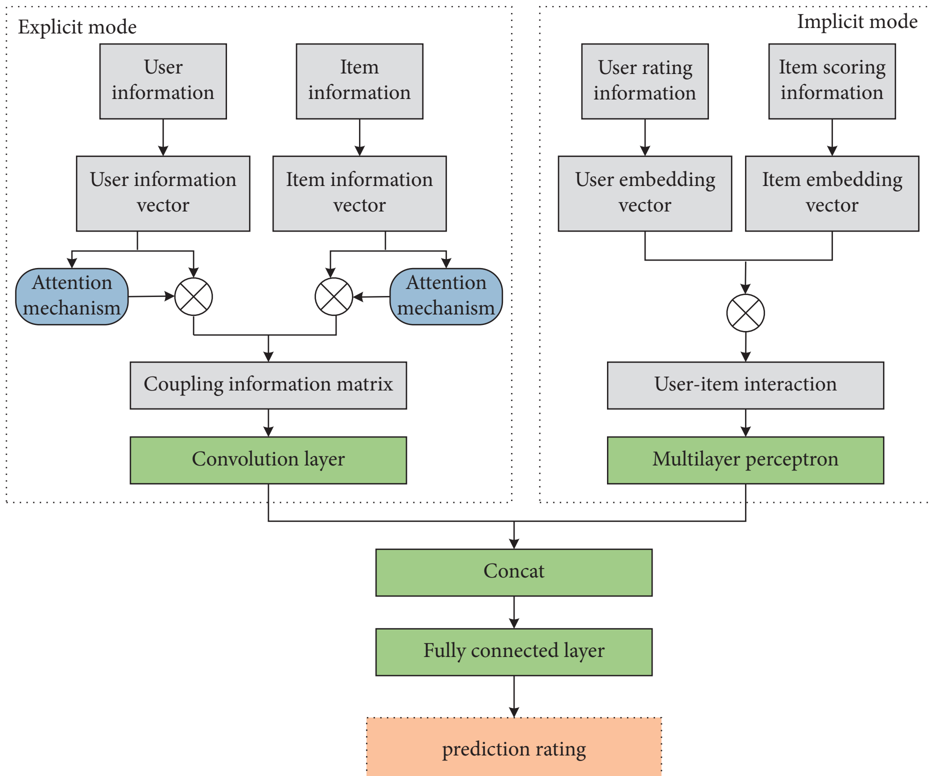

Figure 7: Coupled collaborative filtering model.

$$y_2 = P_{ai} = \overline{R}_a + \frac{\sum_{b \in NB_{ua}} sim\ (a,b) * \left(R_{bj} - \overline{R}_b\right)}{\sum_{b \in NB_{ua}} sim(a,b)}, \tag{10}$$

where *sim* (a, b) is the similarity calculated based on the user profile. NB_{ua} generates the set of nearest neighbours of user a based on the similarity of the user profile. R_{bj} is the rating of item j by user b, $\overline{R}_a$ and $\overline{R}_b$ is the average rating of users a and b.

Then, the score predictions based on the image analysis and the improved collaborative filtering algorithm were fused using appropriate weights to obtain the composite score predictions.

$$Y = \alpha y_1 + (1 - \alpha) y_2, \tag{11}$$

where α is a weighting factor determined experimentally and takes values in the range [0, 1]. We assume $\alpha = 0$, the similarity calculation only considers the method based on portrait analysis. Otherwise, the similarity calculation only considers the ways based on collaborative filtering. The value of α in this paper is 0.6. To train the model, gradient descent and other optimisation methods commonly used in the field of machine learning were used, where the loss function was calculated using a cross-entropy loss function. The cross-entropy loss function is characterised by a nonlinear mapping of the data to the (0, 1) interval, with higher probabilities for larger values and lower probabilities for smaller values, in line with the regression concept of recommendation systems. The loss function is

$$L(y_1, y) = -y \ln\ (y_1) - (1 - y) \ln\ (1 - y_1), \tag{12}$$

3. Result Analysis and Discussion

This paper uses the well-known recommendation system test datasets MovieLens1M and Book-Crossings to conduct experiments. A validation set of 99 randomly selected negative samples together with one positive sample retained during the training process is used to test the effectiveness of the models for comparison. The evaluation metric used was the top-K hit rate HR@K normalised discounted cumulative gain NDCG. HR@ K was used to calculate the probability of the test item in the TOPK recommended item list.

$$\text{HR@K} = \frac{\#\text{hits@}\,K}{|T|}, \tag{13}$$

where #hits is the number of hits of the recommended result in the test set T.

The normalised discounted cumulative gain NDCG calculates hit positions by assigning higher scores to the top ranking:

$$\text{NDCG@}K = D_k \sum_{s=1}^{K} \frac{2^{P_s} - 1}{\log_2\ (s+1)}, \tag{14}$$

where p_s is the relevance of the recommended result at position s and D_k is the normalisation factor. In the experiment, K is taken to be 10 and $p_s \in \{0, 1\}$, with p_s taking 1 if the recommended result at position *s is* in the recommended entry and 0 otherwise.

3.1. Experimental Data. The MovieLens 1M dataset contains information on 6040 users and 3952 movies, all rated on a 5-point scale. Each user is guaranteed to place at least 20 films to ensure that the density of data is sufficient to support the recommendation system. The user information in the dataset includes gender, age, occupation and postcode, and the movie information provides for the type of movie, which is used as input to the explicit model. The user's rating information of the movie is binarised as the input of the implicit model. If the user has a score on the item, the interactive data is marked as 1. If the user does not rate the item, the interactive data is marked as 0.

The Book-Crossings dataset contains 1.1 million ratings of 270,000 books by 90,000 users, with ratings ranging from 1 to 10 and including implicit ratings. For this experiment, the age, nationality and city of the user are used, along with the author, year of publication and publisher of the book. For the input to the implicit model, the user's rating information for the book is binarised. The interaction data is marked as 1 if the user has rated the item. It is marked as 0 if the user has not rated the item. Because there are too many different entries in each type of data of users and books, the dimension of input data will be too large by using independent heat coding. Therefore, this paper uses the direct numerical method to input the data into the model.

3.2. Ablation Experiments. To verify the improvement effect of attention mechanism and portrait analysis technology on the model, the test results of this model (model 1) were compared with other models. Among them, model 2 represents a coupled collaborative filtering model without introducing attention mechanism and portrait analysis technology. Model 3 represents a coupled collaborative filtering model with only attention mechanism. Model 4 represents a coupled collaborative filtering model with only portrait analysis technology. The sparse Book crossings data set is selected for the experimental data. The results of HR@10 and NDCG@10 are shown in Table 1.

Compared with model 2, models 1, 3, and 4 improve the hit rate and NDCG index by introducing attention mechanism and portrait analysis technology. By introducing attention mechanism, model 3 improves the hit rate and NDCG index by 12.5% and 8.38% respectively. By introducing portrait analysis technology, model 4 improves the hit rate and NDCG index by 6.87% and 5.95% respectively. The experimental results show that attention mechanism and portrait analysis technology have an obvious effect on the recommendation effect of coupled collaborative filtering model on sparse data sets. Among all the models, the proposed model has the best recommendation effect. The attention mechanism and portrait analysis technology can cooperate with each other to effectively improve the performance of the coupled collaborative filtering model.

Table 1: Ablation experiments.

Models	HR@10	NDCG@10
Model 1	0.1478	0.1005
Model 2	0.1194	0.0907
Model 3	0.1343	0.983
Model 4	0.1276	0.0961

3.3. Comparative Experiments. To test the performance of the proposed models, the experimental results are compared with the CF-UEP model in the literature [20], the CoupledCF model in the literature [21], the EACoupledCF model in the literature [22], the DCF model in the literature [23] and the model based on collaborative filtering and picture analysis in the literature [24]. The comparison results of several models on the MovieLens 1M dataset and the Book-Crossings dataset are given in Figures 8 and 9, respectively.

Figures 8 and 9 demonstrate that the proposed model is based on a coupled collaborative filtering model, which is optimised in terms of recommendation effectiveness by introducing attention mechanisms and portrait analysis techniques. Compared to literature [20], the model in this paper and literature [21–23] all use a collaborative filtering model that incorporates explicit and implicit feedback information, and their recommendation results are superior to those of the separate models. Compared to literature [23], the model in this paper and literature [21] and literature [22] all use coupled collaborative filtering models, and their recommendation results are better than the decomposed collaborative filtering model in literature [23]. The literature [22] improves the recommendation effect of the literature [21] by introducing an attention mechanism. Based on this, this paper presents the technique of portrait analysis to achieve accurate recommendations by matching the characteristics of users' preferences and resources. Although the literature [24] also introduced user portrait techniques, its collaborative filtering model is explicit, so the recommendation effect is not ideal.

In addition, to investigate the effect of K values on the models in top-K evaluation, experiments were conducted in the literature [21, 22] with this model on the MovieLens 1M dataset. The experimental results of HR and NDCG for the three models are shown in Figures 10 and 11, assuming that K is taken as 5, 10, 15, and 20, respectively.

When K is 5 and 10, literature [22] and this paper's model introducing the attention mechanism will have some advantages in HR. However, when $K = 15$ and 20, the hit rate difference between the literature [21], the literature [22] and this paper's model is not much, and even the hit rate of the literature [22] model is slightly inferior to that of the literature [21] model. The reason is that the introduction of attention mechanism increases the complexity of the network to a certain extent. Attention mechanism can extract the key degree of each attribute. However, when the K value increases, the key degree of each attribute does not play a crucial optimisation role in the recall rate top-K index, but makes the subsequent feature learning difficult. The hit rate

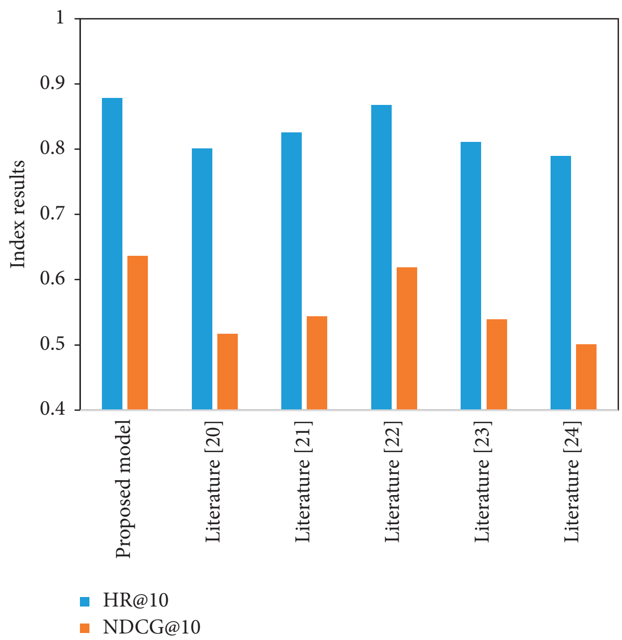

FIGURE 8: Comparison of models in MovieLens 1M.

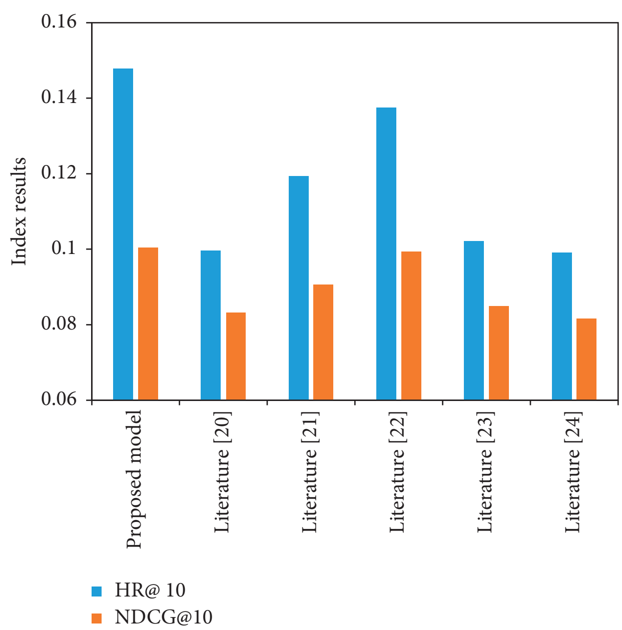

FIGURE 9: Comparison of models at book-crossings.

of the proposed model is slightly higher than that in literature [21], which is mainly the contribution of portrait analysis technology.

The NDCG of literature [22] and the proposed model is always better than that of literature [21]. This shows that no matter how the K value changes, the mining of attribute criticality will have a positive feedback on the correctness of the arrangement position of the recommended targets, making the performance of the model more user-friendly in practical engineering applications. The introduction of portrait analysis technology makes the advantages of the proposed model more obvious.

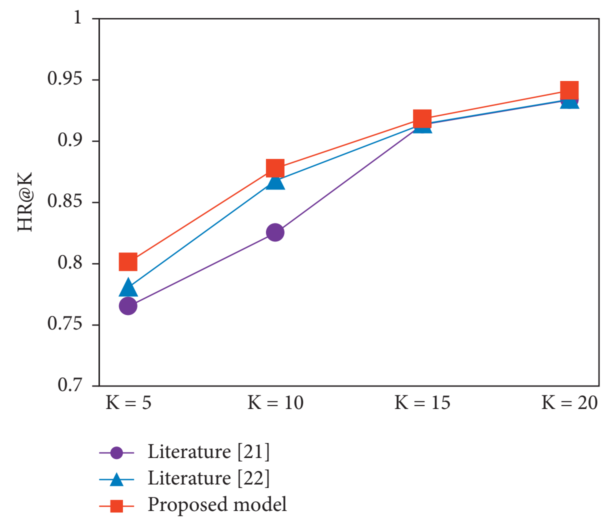

FIGURE 10: Experimental results of HR@ K for the three models.

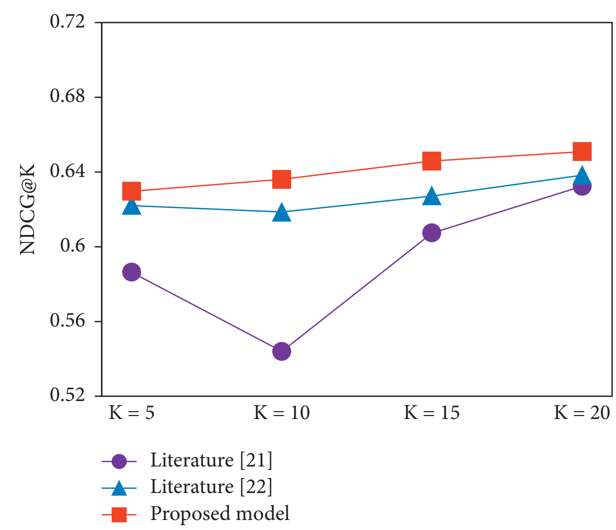

FIGURE 11: Experimental results of NDCG@ K for three models.

4. Conclusion

The integration of industry and education has become a deep-seated driving force for the current structural reform on the supply side of human resources. It has important implications to the overall improvement of education quality and the expansion of employment and entrepreneurship under the new situation. The framework design, knowledge tree construction and resource production in the construction of a professional teaching resource library for vocational education should aim to meet the needs of talents integrated with industry and education. Both learning and teaching should reflect user-centred services and support personalised learning and teaching. Still, we need to further strengthen the semantic mining and interconnection of cross-media, multi-modal, and multigranularity information resources. By deepening the integration of portrait technology and knowledge services, a series of knowledge products and services are accurately embedded into the knowledge learning and scientific research of users of the shared resource platform.

Data Availability

The labeled dataset used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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