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RESEARCH ON THE RECOMMENDATION SYSTEM OF MUSIC E-LEARNING RESOURCES WITH BLOCKCHAIN BASED ON HYBRID DEEP LEARNING MODEL

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Abstract. Learners are confronted with an ever-growing array of diverse and complex educational resources as music education increasingly moves to online platforms. Traditional resource curation methods, which rely heavily on educators, fall short of meeting the dynamic needs of modern students. To address this issue, we present a novel recommendation system for music e-learning resources that combines the power of blockchain technology with a hybrid deep learning model. Our model combines blockchain's robust security and transparency features with advanced deep learning algorithms, enhancing the personalization and efficiency of resource recommendations. A backpropagation neural network with K nearest neighbor classification, traditional collaborative filtering (CF), and an improved CF algorithm are used in the hybrid approach. For the back propagation neural network algorithm, K nearest neighbor classification algorithm, traditional collaborative filtering (CF) and improved CF algorithm, the accuracy rate of improved CF algorithm is higher, reaching 95%. Comparing the proposed model with the association rule-based recommendation model and the content-based recommendation model, the model constructed in this study received high evaluation from experts, with an average score of 98, and more than 97% of them gave a high score of 95 or more, and the evaluation of experts tended to be consistent. Overall, the model proposed in this study can make better recommendations for music education learning resources and bring users a good learning experience, so this study has some practical application value. This research demonstrates a highly effective, blockchain-enhanced recommendation system for music e-learning resources. Our model has significant practical value and potential for adoption in online music education platforms because it provides tailored educational content and an enhanced learning experience.

Key words: music education; recommendation algorithm; learning resources; CF; online education

1. Introduction. The emergence of online learning platforms has altered the landscape of music education in recent years. This digital transition has resulted in an extraordinary profusion of e-learning materials, providing students with a variety of material. The successful curation and suggestion of materials matched to individual learning needs and tastes, on the other hand, is a substantial difficulty. Due to the diverse types of music knowledge and the rich connotation of knowledge, offline music education can no longer satisfy the learning requirements of students, and there is an urgent need to develop online music education so that students can study independently at any time [1]. With the development of online music education, more and more platforms are offering music education resources, and the number of music education resources is growing extremely fast. The traditional way of screening is that teachers screen the resources in advance and recommend the screened resources to students, or students spend some time to screen them themselves [2]. However, the number of resources is too large and the quality of resources varies, and it is very time-consuming to find the right high-quality resources from the huge resource base [3]. In view of this, a large number of scholars have studied the recommendation algorithms of online education repositories, and common resource recommendation methods include content-based, Collaborative Filtering (CF), association rule-based, utility-based, knowledge-based, and hybrid recommendation algorithms [4].

In order to provide learners with high-quality resources that are more suitable for learners' own characteristics, this study chose hybrid recommendation algorithms for model design. In this study, the hybrid algorithm music education recommendation system structure will be designed by using LFM algorithm in the overall recommendation module; in the interest recommendation module, real-time recommendation algorithm based on learners' evaluation scores; in the similar resource recommendation module, CF and content-based recommendation algorithm will be used; in the high rating rate resource recommendation module, learner rating-based

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The recommendation algorithm based on the quantity of times the learner rated the resource is used in the high rating rate resource recommendation module. Finally, the performance of the model constructed in this study will be evaluated and comparatively analyzed for validating the value of the proposed model in music education. Traditional techniques of resource selection, which mostly rely on instructors, are becoming increasingly insufficient in this dynamic and expanding digital environment.

To solve this issue, we provide an innovative, blockchain-enhanced recommendation engine created exclusively for music e-learning resources. This system uses developing blockchain and hybrid deep learning models to transform how learners access and engage with online music education information. Blockchain technology, which is well-known for its safe and transparent data processing, provides a strong framework for organizing and suggesting educational resources. At the same time, hybrid deep learning models offer advanced analytical capabilities for personalizing content recommendations, ensuring that learners obtain the most relevant and valuable materials. main contribution of the study rely on,

1. Our study is notable for incorporating blockchain technology into the recommendation system. This connection improves the resource suggestion process's security, transparency, and dependability, ensuring that learners receive trustworthy and high-quality content.
2. The model combines complex techniques such as backpropagation neural networks and K closest neighbor classification with collaborative filtering methods to create a hybrid deep learning model. When compared to standard models, our hybrid approach greatly enhances the accuracy and relevance of resource recommendations.

2. Related works. With the newer iterations of online technology, music education is becoming more and more important. Bath N believes that receiving music education is the right of every individual and should not be marginalized from setting courses [5]. Offline music education has emerged, and Kruse and Hill look to inform online education in popular music with a study that provides a detailed analysis of music videos. This study first analyzes the content of music videos, then extracts useful music techniques from them, and finally stores them in a library of music resource learning materials [6]. Camlin et al. explore the impact on learners of the shift from offline to online education models and predict a possible educational crisis, suggesting appropriate responses to this crisis [7]. Daubney with Fautley M, in their study of online music education, found problems with the assessment of student scores and, in light of this, made recommendations for specific teacher tasks and expected teachers to be trained to adapt to the online education model [8]. Cheng and Lam et al. found that the model of online education can also have an impact on teachers, who can be unable to adapt to online education, leading to anxiety and other psychological The teachers are unable to adapt to online education, which can lead to anxiety and other psychological problems [9].

Domestic online education is still in its preliminary stage and there are still a lot of problems that need settling. A large quantity of scholars has paid attention to the problem of recommending learning resources, and there has been a large amount of mature research in the field of network recommendation. Zhao P et al. constructed a new recommendation model based on the recurrent neural network algorithm mixed with the point-of-interest recommendation algorithm. The recurrent neural network assisted the ability of the point-of-interest recommendation method to link the context and predict the data more effectively [10]. Li et al. introduced a multi-objective optimization algorithm to improve the traditional recommendation model for solving the resource overload problem in an online educational system. The results showcased that the model was effective in improving the accuracy and novelty of resource recommendations [11]. Mou et al. presented a new model with the expectation of using it to explore the impact of recommendation algorithms, privacy protection, etc. of short video platforms on users. The research model uses equation modeling to analyze the questionnaire information. The results show that the recommendation algorithm has an impact on users' behaviors and affects their sustained engagement time [12]. Liang and Yin found that the quality of online educational resources is uneven and users' trust in the resources is low. In view of this, they proposed a new recommendation algorithm, expecting to improve users' trust. The algorithm first classifies educational resources and filters invalid educational resources. Then the Kalman filtering method is used to reduce the noise of educational resources and generate a list of highly similar resources for recommendation. The final experimental results show that this model improves users' trust in learning resources [13].

In summary, facing the shortcomings of music education online development, scholars need to conduct a

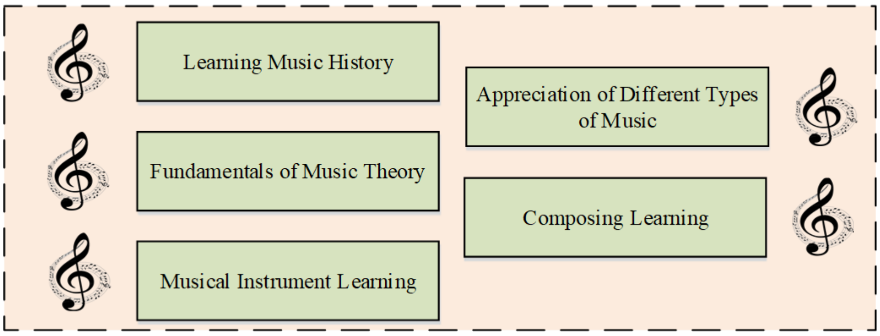

Fig. 3.1: Knowledge points of music education online course resources

lot of research to improve this. As for the deficiencies in music resource recommendation, a large number of recommendation algorithm studies have been relatively mature, so this study designs a model for music education based on hybrid algorithms, expecting to enhance the quality of resource recommendation and meet the characteristics of student learning, so as to improve students' music literacy.

3. Hybrid algorithm music education resource recommendation system design.

3.1. Hybrid algorithm music education recommendation system structure design. The purpose of this research is to use a hybrid algorithm model to filter recommendations for web resources. In order to better design the hybrid recommendation model, the first step is for designing the recommendation function structure of the recommendation system. The first step of the structure design is to understand the characteristics of the web resources, then to consider the aspects of learners' ratings and learners' interests, and finally to select a suitable recommendation algorithm on this basis. This time, the model divides the knowledge points of music education online course resources into five parts, as shown in Figure 3.1.

As shown in Figure 3.1, the web resources knowledge points are divided into five modules, which are music theory basics, instrument learning, music history learning, different types of music appreciation and composition learning [14]. The five modules involve the cross-application of knowledge points, so it can be seen that learners need to learn multiple knowledge points meanwhile, and the quantity of recommended resource knowledge points in this study is designed with reference to this principle [15]. This method first requires labeling the above five learning resources knowledge points, and the multi-label web resources will have slightly different knowledge point biases when facing different people. Therefore, the study uses the TF-IDF algorithm to assign the weights of knowledge points to accommodate the different labeling needs of various populations. Based on this, the cosine similarity is used to classify the learning resource base, according to the similarity, to tailor the knowledge base for learners and recommend similar resources. The design of recommendation structure from the perspective of learners' ratings is a reasonable direction, but the evaluation scores do not exactly match the quality of learning resources, which can lead to interference with the algorithm. In view of this, this study will introduce another metric: the frequency of evaluation of resources. For this study, in terms of real-time recommendations, the last few ratings of learners are combined with the current resource ratings, and a list of recommendations is generated for similar resources in both. For newly registered users, the system also has a solution. When a new user registers, the system automatically recommends five interest modules for selection, and the user's selection becomes a feature tag, and the system then classifies the tags and sorts and recommends similar resources according to their scores from high to low. According to the previous recommendation system design idea, the flow chart of recommendation function structure is designed as shown in Figure 4.1.

The recommendation system is mainly divided into six modules, which are overall recommendation, interest recommendation, high-frequency resource recommendation, latest recommendation, resource display, and similar recommendation. After the user logs in, the overall recommendation module will show the user a list of resources generated based on historical ratings and the system's collaborative filtering algorithm. The interest recommendation module mainly creates a list of resources needed by learners based on current ratings and historical ratings. The High Score Recommendation module generates a list of learning resources based on the frequency of users' ratings, from highest to lowest. Latest recommendation is to generate a list of learning resources from near to far based on the publisher's release time. The Resource Display module mainly displays the resources so that learners can browse, rate and label the resources. The similarity recommendation module analyzes and organizes similar resources, and generates a list of resources with high similarity. In summary, when a user logs in, the system will recommend to the learner through a mixture of comprehensive recommendation, high frequency resource recommendation, interest recommendation, similar recommendation and latest recommendation.

The login and resource display generate data information, which is because during the login, users select the learning knowledge points according to their preferences, and in the comprehensive recommendation module, they rate the learning resources and other operations. The information from these two parts will be used as the basis for recommendations. The other modules are all about the use of information, based on the data information generated by the user, into the recommendation system for analysis and calculation, and then feedback to the user.

3.2. Hybrid algorithm music education recommendation model construction. The previous section is the structural design of the whole recommendation system for music education, and the later section will introduce in detail the hybrid approach of algorithms and multi-algorithm model construction in the recommendation resource system. Next, the similar recommendation module will be explained in detail. Word frequency -The term frequency-inverse document frequency (TF- IDF) is an algorithm for information retrieval and data mining The common weighting technique of [16]. The similarity module mainly uses a statistical algorithm TF-IDF, which operates in a special analytical mode for semantic contexts, where the TF part is expressed as shown in equation 3.1.

$$TF_{i,j} = \frac{n_{i,j}}{n_{*,j}} \tag{3.1}$$

As shown in equation 3.1, where is used to represent the sentence; $jn_{i,j}$ is used to represent the quantity of occurrences of in ij; $n_{*,j}$ denotes the total quantity of words in j; and the word frequency of i in j is represented by $TF_{i,j}$. After this operation, it is also necessary to express the weight of the words in terms of IDF, whose expression is shown in equation 3.2.

$$IDF_i = \log\left(\frac{N+1}{N_i+1}\right) \tag{3.2}$$

As shown in equation 3.2, N denotes the total quantity of sentences; N_i denotes the total quantity of sentences containing the word i. The overall formula of the unified calculation method is shown in equation 3.5.

$$TFIDF_{i,j} = TF_{i,j} \times IDF_i \tag{3.3}$$

As shown in equation 3.3, where TF localizes the word frequencies and then uses IDF to assign the weights of the words. The similarity recommendation module also uses the Collaborative Filtering recommendation (CFR) algorithm, which can be represented by $U = \{u_1, u_2, \ldots, u_i, \ldots, u_m\}$ for the set of learners m and $I = \{i_1, i_2, \ldots, i_i, \ldots, i_n\}$ for the set of resources [17]. The scoring matrix is shown in equation 3.4.

$$\begin{bmatrix} R_{11} & R_{12} & \cdots & R_{1n} \\ R_{21} & R_{22} & \cdots & R_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ R_{m1} & R_{m2} & \cdots & R_{mn} \end{bmatrix} \tag{3.4}$$

As shown in equation 3.4, R_{ij} represents the rating of by the user i_j . Equation 3.5 demonstrates the formula for calculating the cosine similarity.

$$\mathrm{sim}(u,v) = \cos(\overrightarrow{I_u}, \overrightarrow{I_v}) = \frac{\overrightarrow{I_u} \cdot \overrightarrow{I_v}}{\|\overrightarrow{I_u}\| \times \|\overrightarrow{I_v}\|} = \frac{\sum_{i=1}^{n} R_{ui} R_{vi}}{\sqrt{\sum_{i=1}^{n} R_{ui}^2} \times \sqrt{\sum_{i=1}^{n} R_{vi}^2}} \tag{3.5}$$

As shown in equation 3.5, u and v denote users and i denotes resources; $R_u i$ serves as the rating of u to i and R_{vi} serves as the rating of v to i. The Pearson correlation coefficient is then introduced for calculating the similarity between u and v, and the expression is shown in equation 3.6.

$$\operatorname{sim}(u, v)=\frac{\sum_{i \in I_{uv}}(R_{ui}-\overline{R_u})(R_{vi}-\overline{R_v})}{\sqrt{\sum_{i \in I_{uv}}(R_{ui}-\overline{R_u})^2} \times \sqrt{\sum_{i \in I_{uv}}(R_{vi}-\overline{R_v})^2}} \tag{3.6}$$

As shown in equation 3.6, $\overline{R_u}$ denotes the average of all resource ratings by u and $\overline{R_v}$ denotes the average of all resource ratings by v ; the set of resources jointly evaluated by u and v is denoted by $I_u v$. Based on this, this study also introduced a correction factor α to improve the calculation of Pearson's correlation coefficient. The improved expression is shown in equation 3.7.

$$\operatorname{sim}'(u, v)=\frac{\min(|I_u \cap I_v|, \alpha)}{\alpha} \times \operatorname{sim}(u, v) \tag{3.7}$$

As shown in equation 3.7, a natural number α can be obtained by training; $I_u \cap I_v$ represents the intersection between the learners' ratings and $|I_u \cap I_v|$ represents the quantity of co-rated resources. Equation 3.7 can also be transformed to equation 3.8.

$$\operatorname{sim}'(u, v)=\begin{cases}\operatorname{sim}(u, v), & \text{if } |I_u \cap I_v| \geq \alpha \\ \frac{|I_u \cap I_v|}{\alpha} \times \operatorname{sim}(u, v), & \text{if } |I_u \cap I_v|<\alpha\end{cases} \tag{3.8}$$

As shown in equation 3.8, when $|I_u \cap I_v|$ is smaller than the correction factor α, the similarity needs to be corrected to prevent the transition prediction of the algorithm, and vice versa, no correction is needed. In addition to considering the similarity for ratings, the similarity between learners can also be considered by classifying the rating levels. Introduce the rank correlation formula as shown in equation 3.9 [18].

$$\operatorname{sim}(u, v)=\frac{\sum_{i \in I_{uv}}(Rank_{ui}-\overline{Rank_u})(Rank_{vi}-\overline{Rank_v})}{\sqrt{\sum_{i \in I_{uv}}(Rank_{ui}-\overline{Rank_u})^2} \times \sqrt{\sum_{i \in I_{uv}}(Rank_{vi}-\overline{Rank_v})^2}} \tag{3.9}$$

As shown in equation 3.9, where the set of resources jointly evaluated by u and v is represented by I_{uv} . Firstly, the learning resources are labeled with corresponding labels. Then the semantic frequencies and weights are calculated according to the TF-IDF algorithm. And finally, the similarity of the three resources is calculated by cosine similarity. The recommendation system proposed in this study lists the similar resources on this basis. In the overall recommendation section, the semantic modeling algorithm is applied, which is based on finding hidden features that are not easily detected in the learners and predicting how the learners rate the recommended resources. The semantic model algorithm uses the idea of regression and its expression is shown in equation 3.10.

$$\hat{R}_{m \times n}=P_{m \times k}^T \cdot Q_{k \times n} \approx R \tag{3.10}$$

As shown in equation 3.10, where $\hat{R}_{m \times n}$ is used to represent the prediction matrix, this matrix is calculated by learning the original matrix R using the algorithm of regression.

$$C=\sum_{(u,i) \in R_0}(R_{ui}-\hat{R}_{ui})^2+\operatorname{Reg}=\sum_{(u,i) \in R_0}(R_{ui}-P_u^T \cdot Q_i)^2+\lambda \sum_u\|P_u\|^2+\lambda \sum_i\|Q_i\|^2 \tag{3.11}$$

As shown in equation 3.11, where Q and R denote two matrices, u denotes a user, and i denotes a different resource. R_{ui} and $\hat{R}_{ui}$ denote a point in the matrix. In order to avoid overfitting, the regularization operation [19] is introduced.

In the first, the learning matrix of users is established; in the second step, the real ratings of users in the database are input into the matrix. In the third step, for the unrated blank part, the system automatically uses the semantic model algorithm for predicting the user's rating; in the fourth step, the system recommends the user according to the rating level. The interest recommendation is obtained by combining the high frequency recommendation and the latest recommendation, in the latest recommendation u denotes the learner, K serves as the quantity of ratings, the set of resources is defined as IK, the set of similar resources is defined as JK , and the cosine similarity calculation formula is introduced again, as shown in equation 3.12.

$$\operatorname{sim}(m,n)=\frac{\sum_{i=0}^{k}(f_{mi}\times f_{ni})}{\sqrt{\sum_{i=0}^{k}f_{mi}^{2}}\times\sqrt{\sum_{i=0}^{k}f_{ni}^{2}}} \tag{3.12}$$

As shown in Exhibit 3.12, m and n represent any two resources in the set IK; f_{mi} represents the rating prediction for m and f_{ni} represents the rating prediction for n; i represents the ith learner. The high frequency recommendation is a ranked recommendation of the resources in the similar set, and this ranking before and after the computational expression is shown in equation 3.13.

$$P_{u,j}=\frac{\sum_{i\in IK}(\operatorname{sim}(j,i)\times S_i)}{\text{sim\_sum}}+lg\max(\text{highscore},1)-lg\max(\text{lowcore},1) \tag{3.13}$$

As shown in equation 3.13, a resource in the set of similar resources JK is represented by j. $P_{u,j}$ indicates the priority of the resource.

In the Linux environment module there are database with different types of back-end services, and also logs can be generated and processed in this module. Web uses a front-end and back-end separation method for services, and users can log in at the Windows remote end to access different pages[20]. The database is the foundation for the system's correct operation; the Web allows users to log in and provides services such as the presentation of learning resources, user ratings, and so on. The back-end service analyzes and processes system storage logs in order to provide a list of resource suggestions using a recommendation algorithm.

4. Evaluation analysis and comparison of hybrid algorithm music recommendation models.

4.1. Performance testing of hybrid algorithm music education recommendation model. In this study, 50 students in a flipped music education classroom were chose for taking part in in an experiment using the recommendation system. To objectively demonstrate the function of the recommendation system, the students in the selected classroom included three levels of learning: college students, graduate students, and doctoral students. Introducing accuracy and recall as evaluation indicators, we analyzed the recommendations of four modules: similar recommendation, interest recommendation, overall recommendation, and high-frequency recommendation. The changes in accuracy and recall with the number of recommendation list resources are shown in Figure 4.1.

From Fig. 4.1a, it can be seen that the recall rate of each module recommendation algorithm increases steadily with the increase of the quantity of recommendation list resources, among which the recall rate is similar recommendation module, overall recommendation module, high frequency recommendation module, and interest recommendation module in order from high to low; the recall curve of the recall rate of interest module recommendation algorithm fluctuates relatively more, while the rest are relatively stable. Figure 4.1b illustrates that the accuracy rate of the four module algorithms increases when the number of recommended resources is 15 to 20; with the increase of the quantity of recommended list resources, the accuracy rate of each module recommendation algorithm shows an overall decreasing trend, in which the accuracy rate is similar recommendation module, overall recommendation module, high frequency recommendation module, and interest recommendation module in order from high to low. This experiment continues to introduce the F1 value, which is a comprehensive index of recall and accuracy, to judge the number of resources in the best recommendation list, as shown in Figure 4.2.

As can be seen from Figure 4.2, when the number of recommendation list resources is from 5 to 20, the F1 values of all the four module recommendation algorithms increase rapidly; when the number of recommendation list resources is from 20 to 25, the F1 values of the four module recommendation algorithms rise gently; when the number of recommendation list resources is from 25 to 35, the F1 values of the similar recommendation module and the overall recommendation module begin to decline, and the F1 curves of the interest module and

(a) Change in accuracy

(b) Change in recall rate

Fig. 4.1: The variation of recommendation accuracy and recall rate in different sections with the number of recommendation list resources

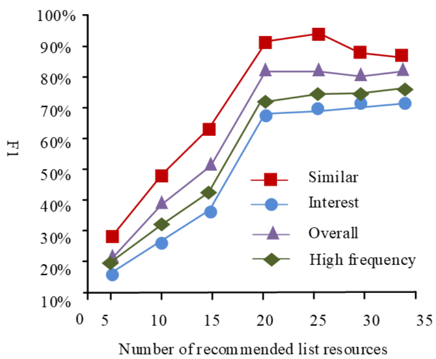

Fig. 4.2: The variation of recommended F1 values for different sections with the number of recommended list resources

the HF module continue to rise gently When the quantity of resources in the recommendation list is between 25 and 35, the F1 values of the similar recommendation module and the overall recommendation module start to decline, while the F1 values of the interest module and the high frequency module continue to rise gently, but the rise is smaller and tends to be horizontal. Overall, when the quantity of resources in the recommendation list is 25, the F1 values of the recommendation algorithms of the four recommendation modules are higher, which can better recommend for learners and bring into play the advantages of the model proposed in this study, in which the F1 values are similar recommendation module, overall recommendation module, high frequency recommendation module, and interest recommendation module in descending order, with F1 values of 95%, 82%, 73%, and 65%, respectively, indicating that the The similar recommendation module runs the best and has the highest accuracy rate, which brings a better experience to users. For further testing the superiority of the model constructed in this experiment and to conduct a comparative analysis of its performance, 150 sets of recommendation algorithm sample data were selected, the same population size and number of iterations were set, and after several iterations, the common recommendation based on Back Propagation (BP) neural network algorithm, k-Nearest Neighbor (KNN) classification algorithm, the traditional CF recommendation model, and the improved CF algorithm used in the similar recommendation module designed in this study were compared

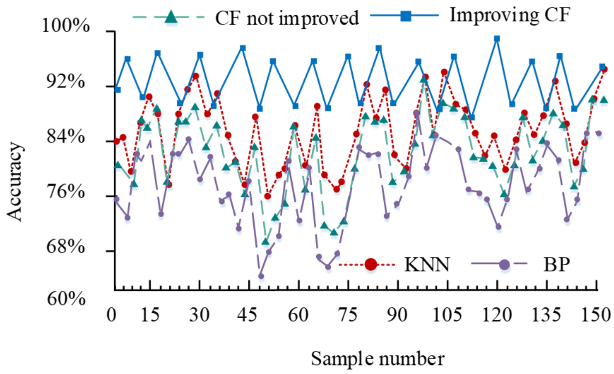

Fig. 4.3: Comparison of accuracy of different model algorithms in different samples

Table 4.1: Page aesthetics evaluation

Page	Extremely beautiful and easy to browse	Beautiful and easy to browse	Beautiful but not easy to browse	Easy to browse but not aesthetically pleasing	Neither aesthetically pleasing nor easy to browse
Navigation	302	169	26	3	0
Registration	185	309	4	1	1
Login	23	400	71	5	1
Interest	34	358	99	7	2
High frequency	187	201	92	20	0
Latest Release	209	189	25	72	5
Resource display	237	205	27	26	5
Overall	398	78	23	1	0

and analyzed, and the accuracy of different model algorithms were compared as shown in Figure 4.3.

Figure 4.3 indicates the accuracy of 100 sets of samples ranged from 60% to 100%. The accuracy of the model based on the improved CF algorithm ranged from 85% to 99%; the accuracy of the model based on the unimproved CF algorithm ranged from 68% to 93%; the accuracy of the model based on the KNN algorithm ranged from 77% to 95%; and the accuracy of the model based on the BP algorithm ranged from 63% to 85%. The accuracy rate based on the improved CF algorithm model was significantly higher than the other algorithms, with an average accuracy rate of 95% for 100 groups; the average accuracy rate for 100 groups based on the unimproved CF algorithm model was 83%; the average accuracy rate for 100 groups based on the KNN algorithm model was 89%; and the average accuracy rate for 100 groups based on the BP algorithm model was 78%. Overall, the improved CF algorithm possesses a higher accuracy rate, not only on the unimproved CF algorithm, but also higher than other algorithms generally applied to recommendation models. Thus, it demonstrates that the improved CF algorithm can be well applied in the music education recommendation model.

4.2. Comparative analysis of hybrid algorithm music education recommendation models. For comprehensively evaluating the superiority of the music education recommendation model proposed in this study, a questionnaire survey will be conducted on 500 users from different aspects to evaluate the hybrid algorithm music education recommendation model proposed in this study, and then the results of the questionnaire survey will be organized and analyzed, as Table 4.1 indicates the evaluation of different users on the aesthetics of the eight pages designed in the method section.

As can be seen from Table 4.1, the overall recommendation page and the login page were more popular

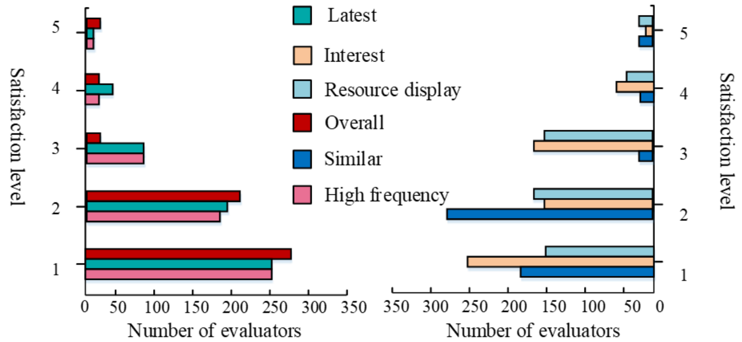

Fig. 4.4: Survey on satisfaction level of different modules in recommendation systems

among users. 398 people rated the overall recommendation page as beautiful and easy to navigate, 78 people rated it as beautiful and easy to navigate, 23 people rated it as beautiful but not easy to navigate, 1 person rated it as easy to navigate but not beautiful, and 0 people gave poor ratings as neither beautiful nor easy to navigate. The login page was rated as beautiful and easy to navigate by 185 people, beautiful and easy to navigate by 309 people, beautiful but not easy to navigate by 4 people, easy to navigate but not beautiful by 1 person, and not beautiful nor easy to navigate by 1 person. Overall, 87.1% of the users rated the pages as beautiful and easy to navigate, beautiful and easy to navigate, which shows that the system pages designed in this study are liked by most users and proves the reasonableness of the pages designed in this study. Next, the six templates designed in this study will be evaluated, as shown in Figure 4.4, which shows the ratings of 500 users on the satisfaction level of each template.

Figure 4.4 illustrates the vertical coordinates of satisfaction level 1 to 5 represent very satisfied, more satisfied, average satisfaction, dissatisfied, and very dissatisfied respectively. It can be seen that users are more satisfied with the interest recommendation module and the overall recommendation module, and the total number of people who are very satisfied and more satisfied with the interest recommendation module is 478; the total number of people who are very satisfied and more satisfied with the overall recommendation module is 472. Overall, users were satisfied with the design of the module, and only 3% of them were dissatisfied or very dissatisfied. For further testing the superiority of the recommendation model for music education constructed in this study, the association rule-based recommendation model and the content-based recommendation model were introduced and compared with the one proposed in this study for analysis, and 20 experts were invited to rate the performance of these three models respectively, as shown in Figure 4.5.

As can be seen from Figure 4.5, the average score of the model in view of association rules is 72, and the score curve fluctuates widely, representing a large difference in experts' evaluation; the average score of the recommendation model based on content is 89, and the score curve fluctuates widely still, with a large difference in experts' evaluation; the model constructed in this study has received a higher evaluation from experts, with an average score of 98, and more than 97% of people give The average score is 98, and 97% of them give a high score of 95 or more, and the fluctuation of the score curve is smaller, and the experts' evaluation tends to be consistent. It proves that the model proposed in this study has superior performance and can give resource recommendations that are more suitable for learners' situations, and has certain applicability in online music education.

5. Conclusion. With the online development of music education, more and more scholars join the research of resource recommendation, and in order to make better recommendations for learners, this research mixes various algorithms to construct a recommendation model for music education resources. In the performance test experiments, the F1 values of the recommendation algorithms of the four recommendation modules are higher when the number of resources in the recommendation list is 25, which are 95%, 82%, 73%, and 65%, respectively, indicating that the table can better recommend for learners when the number of resources is 25,

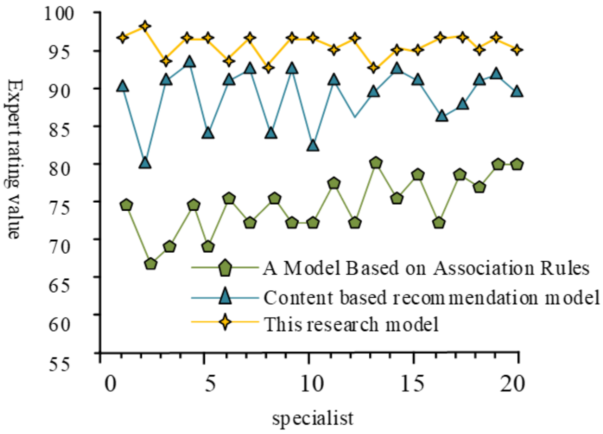

Fig. 4.5: Rating of three models by 20 experts

and take advantage of the model proposed in this study. For the back propagation BP neural network algorithm based on K nearest neighbor Classification algorithm, traditional CF recommendation model, and the improved CF algorithm used in the similar recommendation module designed in this study, the outcomes demonstrate that the improved CF algorithm has a higher accuracy rate of 95%, which shows that the improved CF algorithm can be well applied in the music education recommendation model. In the user questionnaire survey, 87.1% of the users rated the page as beautiful and easy to navigate, more beautiful and easier to navigate; only 3% of the users rated the module as unsatisfactory or very unsatisfactory in terms of satisfaction. In terms of expert ratings, the recommendation model based on association rules and the recommendation model based on content were introduced and compared with the model proposed in this study, and the outcomes indicated that the model constructed in this research received higher ratings from experts, with an average score of 98, and 97% of people gave high ratings of 95 or more, and the fluctuation of the score curve was small, and the expert ratings tended to be consistent. It proves that the model proposed in this study has superior performance and can give resource recommendations that are more suitable for learners' situations, and has some applicability in online music education. However, there are still shortcomings in this study, the update speed of learning resources is slow, and the update speed of resources will be improved on the basis of this study in the future.

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