Hindawi

Retraction

Retracted: Exercise Recommendation Model Based on Cognitive Level and Educational Big Data Mining

Journal of Function Spaces

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Y. Pu and H. Chen, "Exercise Recommendation Model Based on Cognitive Level and Educational Big Data Mining," *Journal of Function Spaces*, vol. 2022, Article ID 3845419, 11 pages, 2022.

Research Article

Exercise Recommendation Model Based on Cognitive Level and Educational Big Data Mining

Yongming Pu [ID] [1] and Hongming Chen [2]

[1]*Teachers' College, Chengdu University, Chengdu 610106, China*
[2]*Chengdu Jing Furong Yi Du School, Chengdu 610061, China*

Correspondence should be addressed to Yongming Pu; puyongming@cdu.edu.cn

There are differences in the learning ability and cognitive ability of different learners. The unified exercises of traditional teaching ignore the differences of learners and cannot meet the personalized needs of learners. Previous recommendation systems focus on the optimization of recommendation performance, rarely clearly reflect the learning state of learners' knowledge points, and there are large errors in the recommendation results. This paper combines the comprehensive cognitive analysis module and the classified knowledge point cognitive analysis module to analyze the cognitive degree of learners' knowledge points. Based on the analysis results, appropriate exercises are selected from the educational resource data to form a list to be recommended. The experimental results show that the exercise recommendation algorithm based on cognitive level and data mining has better recommendation effect and accuracy than the other two recommendation models. The error between the actual difficulty of recommended exercises and the index value is very small. It can recommend an appropriate exercise list according to the actual situation of learners. The teaching comparison results show that the exercise recommendation algorithm can meet the personalized needs of students, recommend targeted exercises, and effectively and greatly improve the learning effect and test scores in a short time. When the motion recommendation algorithm based on cognitive level and data mining has the best recommendation effect, the cognitive module of classifying knowledge points accounts for a large proportion in parameter adjustment. Compared with other recommendation systems, this model has higher accuracy and recommendation effect.

1. Introduction

One of the ultimate goals of school education is to prepare students for employment. For students in school, they have relatively little understanding of the skills required for future work. Therefore, the choice of courses is often lack of pertinence, which cannot play a good support for future employment. In order to avoid the blindness of students' curriculum selection, schools need to combine the specific situation and similar situation of students in school. The learning process of graduates recommends appropriate learning plans for them and makes dynamic adjustments according to the actual situation of students in the learning process. This tailored course teaching method enables every student to get timely guidance in the learning process. It is conducive to the sustainable development of students' learn-ing interests, helps students finally complete the study of this subject, masters the knowledge of relevant fields, and plays a good auxiliary role in the future employment process.

The purpose of knowledge learning lies in application. Continuous application of knowledge is not only an important means to deepen learners' understanding of knowledge points and enhance their mastery of knowledge points but also an indispensable part of education. Limited by educational resources, in the past, educators not only needed to teach dozens of students at the same time but also provided relatively limited exercise resources for students to practice. Educators could not pay enough attention to each student, analyze each student's current mastery of knowledge points, and solve each student's existing problems. Popular education methods and popular education and exercise resources make many learners spend more time finding their own

problems and solving them in the sea of invalid questions [1]. The development of information technology has broadened the way for learners to obtain learning resources. The exercise resources available to learners have increased exponentially. The diversification of exercise types helps learners optimize the whole knowledge system [2]. However, in the face of a large number of exercises, learners also need to pay the cost of mental strength and time to choose exercises, which will lead to the wrong evaluation of the cognitive level of current knowledge points due to the improper selection of exercises, increase the learning burden, and reduce the learning efficiency [3]. Therefore, based on educational data mining, providing personalized educational resources for educators and learners has become a research hotspot in the field of education. The researchers draw lessons from film and television resource recommendation and shopping recommendation and introduce various recommendation algorithms into educational resource recommendation. Among them, the most common recommendation algorithms are collaborative filtering algorithm based on user and item history interaction information, content-based recommendation algorithm, and knowledge information-based recommendation algorithm [4]. These algorithms can provide corresponding recommendations according to different emphases, but with the explosive increase of information and data, the recommendation function of basic recommendation algorithms and models has not met the expectations of users, and further improvement and perfection are an inevitable trend.

The research innovation lies in introducing a cognitive level model to analyze the cognitive status of learners' knowledge points based on educational big data. Through the established exercise recommendation model to achieve effective exercise table recommendation, the test and comparative experimental results of the exercise recommendation model are analyzed. The experimental results show that the motion recommendation algorithm based on cognitive level and data mining has better recommendation effect and accuracy than the other two recommendation models. The error between the actual difficulty of recommended practice and the index value is very small. It can recommend appropriate exercise tables according to the actual situation of learners. The teaching comparison results show that the exercise recommendation algorithm can meet the personalized needs of students, recommend exercises pertinently, and effectively and significantly improve the learning effect and test scores in a short time.

2. Research, Development, and Current Situation of Educational Data Mining and Recommendation System

The explosive growth of information data promotes the research of related retrieval technology. Recommendation system is one of its branches. At present, it has a relatively perfect and mature theoretical organization [5]. The key content of the recommendation system is the recommendation algorithm, which is related to the recommendation

method, performance and results, and the effect of meeting the objectives and requirements. According to the method and algorithm rules, the content-based recommendation algorithm, through collaborative filtering algorithm and the combination of the two are common systems [6]. In order to catch up with the demand of information and data processing, some scholars continue to improve it. Some scholars integrate big data technology into the system and carry out information data mining and recommendation with the help of association rules [7]. Ball proposed that the item recommendation algorithm should consider the practicability of items to users and sort and recommend on this basis [8]. Jiang and Yang establish fuzzy sets in the learning resource recommendation system and use the knowledge reasoning model to extract and recommend the required information [9]. With the diversified development of user needs, Huo et al. have introduced context aware model into mobile social networks to achieve the purpose of user recommendation [10]. In addition, Yunita et al. pay attention to the personalized needs of users, meet the purpose of personalized resources and information data recommendation through algorithm improvement and optimization, and apply it in the fields of film, education, and so on [11].

Educational data mining originated in the late 1980s. In the primary stage of its development, the level of information data acquisition and processing technology is low, which cannot meet its needs to achieve a large number of data acquisition and research. The research methods are limited, and the results obtained are relatively few [12]. The development of computer information technology provides a driving force for educational data mining. At the same time, the rise and scale expansion of online education provide more channels and space for obtaining educational data information. The scale of relevant data expands rapidly, which provides effective and large amounts of data for educational data mining research, and the results are gradually enriched [13]. Wang and Fu take students as the starting point and use cluster model analysis to conclude that there is a large gap in the level of mastering knowledge points among student groups [14]. Other scholars found through the analysis results that the teaching effect will be largely affected by the teaching content and students' own preferences, and the important influencing factor of students' own learning effect is their learning habits [15]. For the research of teaching resources, Bhat et al. pointed out that teaching resources have a hierarchical structure, and there is a correlation between this structure and curriculum characteristics [16]. Zhang et al. pointed out that the main reason for the differences in learning effects lies in the differences of learners. For different learners, educational resources with different emphasis should be provided to realize accurate and personalized retrieval and recommendation [17]. Based on this, Fan et al. have introduced collaborative filtering recommendation algorithm into personalized education recommendation to complete education resource recommendation according to similar interactive information between learners [18]. Through the research on students' learning methods and state, D'Agostino et al. pointed out that exercise is not only an important means to improve learning

effect but also a necessary process. Improving the retrieval of exercise information is to improve learners' learning efficiency [19]. Aziz combines analytic hierarchy process and semantic correlation analysis model to obtain learners' personalized information and complete exercise recommendation on this basis [20]. Chen et al. believe that the problem of exercise recommendation is the transformation of information recommendation. The target area is the students who need exercise recommendation, and the auxiliary scope is the users who have completed the search of relevant historical information. With the help of the auxiliary area information, we can obtain more accurate exercise classification results for the target area, which greatly avoids the recommendation error [21]. Cheng and Bu put forward new recommendation rules from the perspective of learners' probability of doing the right exercise, that is, if learners have more than 50% probability of doing the right exercise, they will make recommendation [22]. The probability setting of this algorithm is enlightening and can achieve the optimal selection in a certain range, but it is not the global optimal. Before recommending exercises, Rianto and Fachrie analyze the current knowledge learning status of students through expert evaluation, form the recent development area with relevant data, and use the gambling machine algorithm to select the exercises with the best effect in this range [23]. The development of deep learning theory has opened up new algorithmic ideas for researchers. MC et al. have introduced deep reinforcement learning theory into the review system, and the constructed learning system can provide interval repetitive learning [24]. In addition, some scholars optimized the network model based on the review model to enhance the performance. To sum up, at present, the optimization and improvement of many exercise personalized recommendation systems focus more on the performance of algorithms, and there are few models that can truly and accurately show learners' current knowledge mastery and learning state, which makes exercise recommendation lack effectiveness and has weak advantages in improving learners' sense of learning experience. In the future development of exercise recommendation algorithm, the position of learners will be improved. The system will not only mention improving performance but also continuously increase personalized service, emphasizing the central role of learners.

3. Construction of Exercise Recommendation Algorithm Based on Cognitive Level and Data Mining

3.1. Idea of Establishing the Overall Framework of Exercise Recommendation Algorithm. The current motion recommendation algorithms of data mining focus on mining association rules in data. By effectively discovering, understanding, and applying association rules, we can make complex and useful knowledge hidden in a large number of sources make greater contributions to the construction of modern education system. The data required by these systems come from students' examination scores accumulated in the teaching process over the years. Through the in-

depth mining of these data, it is not difficult to find that the level of students' grades not only depends on the curriculum itself but also is affected by many aspects, such as the curriculum of the discipline, the formulation of teaching plans, and the order of each course.

Although the era of big data has reduced the time cost of obtaining information, it has increased the time cost of effective information screening and the difficulty of information processing. The purpose of exercise recommendation algorithm is to reduce the time for learners to choose exercises, help learners choose appropriate exercises from massive resources, and gradually enhance their cognitive level. Exercise is the practical link of learners in the process of education. It is an important link to deepen learners' understanding and application of knowledge. It is an unavoidable part for both learners and educators. Many educators believe that learning is a process in which practice makes perfect. Exercises are a tool to help learners improve their proficiency. They should complete as many exercises as possible in a limited time, which will help students deepen the memory of knowledge points. According to the relevant research results, the increase in the number of exercises does not necessarily achieve the effect of improving academic performance. On the contrary, it is very likely that too many exercises will lead to the reduction of learners' thinking time on each question and only know one of the learning knowledge points. In addition, educators need to face a certain number of learners. They are not allowed to give targeted guidance to learners in terms of time and energy. They can only take the situation of most learners as the main basis for teaching feedback and arrange exercises accordingly. For advanced and backward learners, the difficulty of exercises does not meet their current learning state, which greatly affects the learning effect. The same exercises cause different difficulties for different learners. The unified explanation of educators can only solve most of the problems, and some individual problems still become obstacles for learners.

To sum up, the exercise recommendation model not only needs to select suitable exercises for learners in a short time but also needs to clearly distinguish between completed and unfinished, correct, and wrong exercises. This requires the establishment of the exercise recommendation model to truly and accurately reflect the cognitive state of learners and realize effective exercise recommendation for current users in combination with other learners' data information in the relevant range. Figure 1 shows the flow chart of exercise recommendation algorithm based on learners' cognitive level.

The exercise recommendation algorithm based on learners' cognitive level establishes the completed exercise module, marked exercise module, and knowledge point information module, respectively, which provide the input original information. According to the relevant cognitive theories and models, calculate the comprehensive cognitive degree of each learner's knowledge and the cognitive degree of knowledge in different modules, and obtain relevant data information, combined with collaborative filtering algorithm, it can predict the probability that each exercise in the recommended exercise set may be correct. On the basis
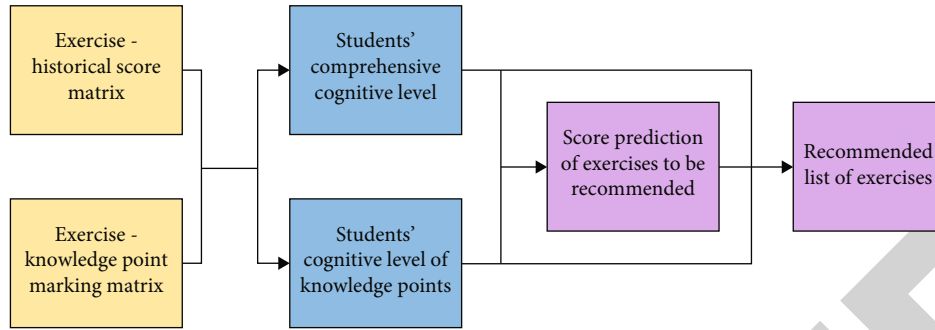
Figure 1: Flowchart of exercise recommendation algorithm based on learners' cognitive level.
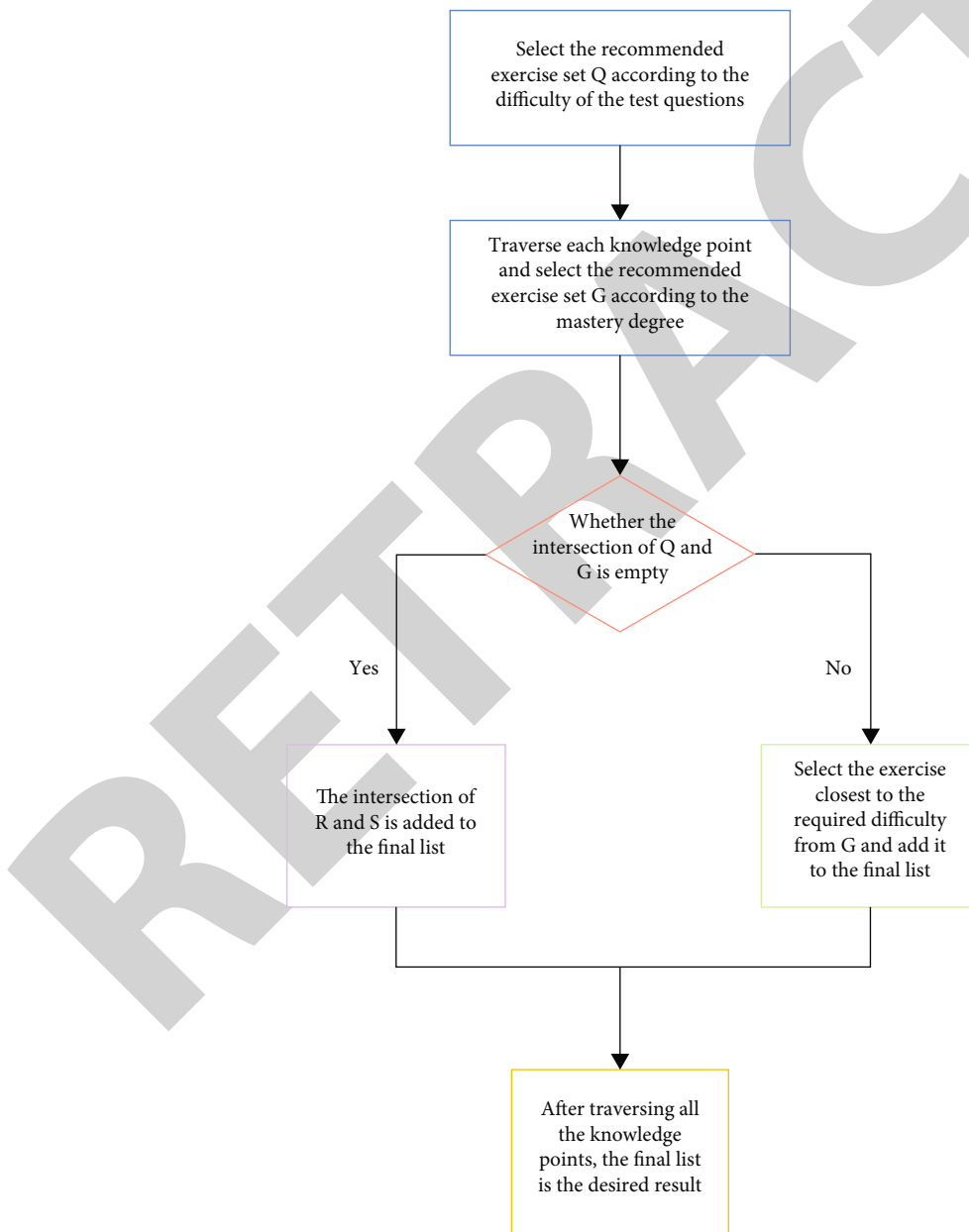

Figure 2: Exercise recommendation algorithm based on cognitive level and data mining.
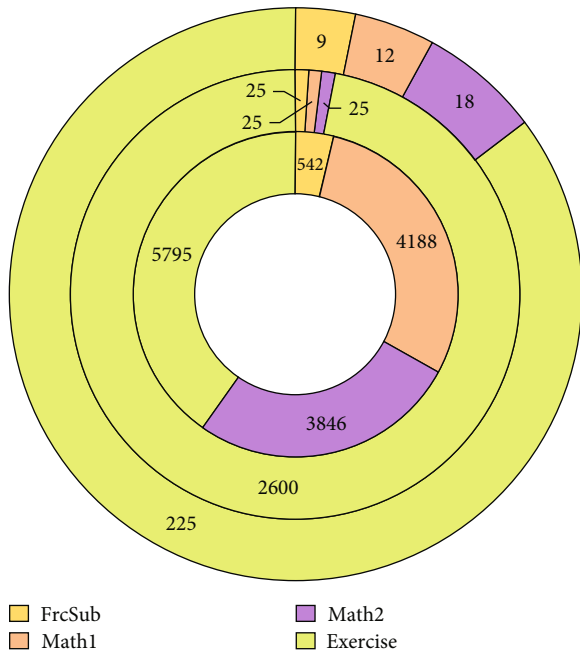
Figure 3: Details of four data sets.

of three aspects of data information, the system can obtain the recommended set of exercises and combine the output.

3.2. Establishment of Exercise Recommendation Algorithm Based on Learners' Cognitive Level Model. The comprehensive cognitive level of learners is their ability to apply the content. Learners' self-evaluation and mutual evaluation can not only promote students' learning of knowledge but also improve students' evaluation ability. Such evaluations should therefore be actively encouraged. Ask students to browse each other's works and put forward revision suggestions according to the rubric. According to relevant cognitive theories and models, the calculation formula of the correct rate of learners a completing exercise b is set as shown in the following formula:

$$P_{ab} = \lambda_b + \frac{1 - \lambda_b}{1 + e^{-1.7\beta_b(D_a - \varepsilon_b)}}, \tag{1}$$

where λ_b represents the probability of learners guessing the exercises correctly without any relevant knowledge; β_b represents the difference degree of exercises; ε_b indicates the difficulty of the exercise; D_a reflects learners' comprehensive cognitive level.

By solving the parameters in formula (1), the learners' cognition of the comprehensiveness of knowledge can be obtained. Let $R_{ab} = 1$ represent the learners' correct answer to the exercise, and $R_{ab} = 0$ represent no correct answer. The new calculation formula of the correct probability is shown in the following formula:

$$P_{ab}^{R_{ab}} (1 - P_{ab})^{1 - R_{ab}}. \tag{2}$$

Set the number of exercises as B, and its maximum like-

lihood function is established as shown in the following formula:

$$L(\beta_b, \varepsilon_b, D) = \prod_{a=1}^{A} \prod_{b=1}^{B} P_{ab}^{R_{ab}} (1 - P_{ab})^{1 - R_{ab}}. \tag{3}$$

Take the corresponding log likelihood function for the next derivative, as expressed in the following formula:

$$\ln L = \sum_{a=1}^{A} \sum_{b=1}^{B} (R_{ab} \ln P_{ab} + (1 - R_{ab}) \ln (1 - P_{ab})). \tag{4}$$

The derivative of the obtained result with respect to the unknown parameter is obtained and its derivative is zero, as shown in the following equations:

$$\frac{\partial \ln L}{\partial \beta_b} = 0, \tag{5}$$

$$\frac{\partial \ln L}{\partial \varepsilon_b} = 0, \tag{6}$$

$$\frac{\partial \ln L}{\partial D_a} = 0, \tag{7}$$

$$1 \leq a \leq A, 1 \leq b \leq B. \tag{8}$$

The cognitive level of various knowledge modules shows the level of learners' mastery of each type of knowledge points. The results of learners' exercises based on this prediction are more targeted. Let the number of knowledge points contained in exercise b be expressed as V and predict the correct state according to the in-depth learning of learners' knowledge points. The calculation is shown in (11):

$$\eta_{ab} = \prod_{v=1}^{V} C_{av}^{J_{bv}}. \tag{9}$$

Among them, the examination status of knowledge takes you is J_{bv}, and its status is divided into examination and nonexamination, that is, when $J_{bv} = 1$ or $J_{bv} = 0$. The state of learners' mastery of knowledge points is described by C_{av}. when the value is 1, learners have mastered knowledge points, and when the value is 0, learners have not mastered knowledge points. In fact, when learners have mastered the knowledge points, they still guess the correct answer due to careless mistakes, or when learners have not mastered the knowledge points. Considering this situation, introduce the careless parameter w into the model and guess the parameter l correctly, as shown in the following formula:

$$P_{ab} = P(R_{ab} = 1 | C_a) = w_b^{1 - \eta_{ab}} (1 - l_b)^{\eta_{ab}}. \tag{10}$$

Among them, the probability of learners not doing right due to carelessness is w_b, and the probability of correctly guessing the answer is l_b. It is also necessary to solve the position parameters in the above formula to obtain the
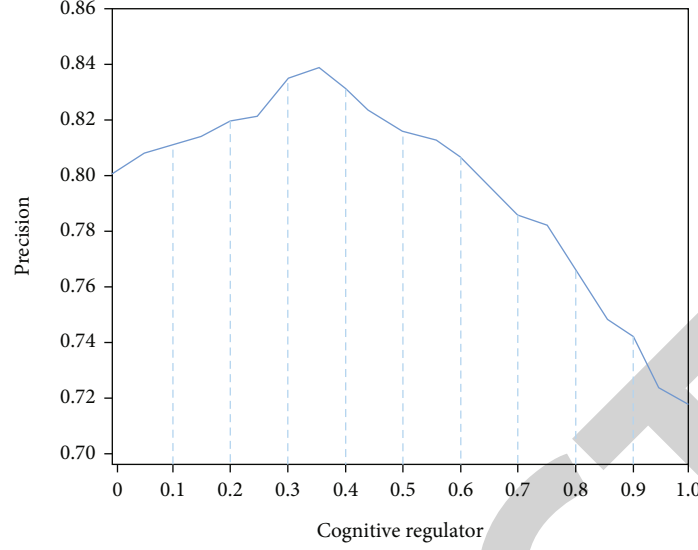
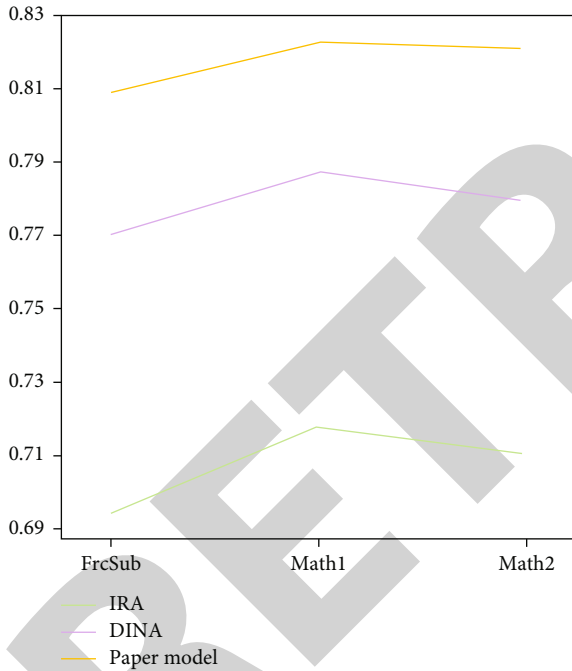Figure 4: The results of frcsub dataset exercise recommendation model under different parameter values.

Figure 5: Prediction and test results of exercise accuracy of three exercise recommendation models in three open data sets.

learners' cognitive level in the classification knowledge points.

There are only two cases for the value of cognitive degree parameters of classified knowledge points obtained through the above. In the actual situation, learners' cognitive state has always changed, which not only has tortuous progress but also is vulnerable to forgetting. Therefore, learners' mastery state of knowledge points cannot be judged by two points, but needs to reflect its continuity. The processing method is to expand the amount of data contained in the learner set with similar knowledge mastery level, and the

parameter C_{av} is processed continuously by taking the set mean. The calculation formula of the level similarity of learners' mastery of knowledge points is as follows:

$$\text{sim}(i, j) = \frac{|M| + |N|}{|M \cup N|} \cdot \frac{1}{|D_i - D_J|}. \tag{11}$$

Among them, the set of exercises with correct answers by both learners is M, and the set of exercises with wrong answers by both learners is N. The comprehensive cognitive level of learners i is described by D_i, sorted according to the similarity calculation results between learners i and other learners, and the top h is selected to form its set of adjacent learners, which is set as H. Replace the original value of the understanding level of continuous classification knowledge points obtained through the following formula:

$$C'_{av} = \frac{\sum_{m \in H} C_{mv}}{h}. \tag{12}$$

Among them, the numerator represents the number of current knowledge points mastered by learners in the adjacent learner set.

After calculating the comprehensive value of learners' cognitive level and the cognitive level value of classified knowledge points, the correctness of the answers to the exercises that have not been done by learners shall be predicted, and the prediction probability of learners' correct answers to the exercises is set as shown in (15):

$$R_{ab} = (1 - \delta)^{\sum J_{bv}} \sqrt{\prod_{v=1}^{V} C_{av}^{J_{bv}}} + \delta \frac{(D_a + 3)}{6}. \tag{13}$$

The cognitive regulation parameter is expressed as δ.

The list of recommended exercises of the model is based on the prediction accuracy and learners' understanding of
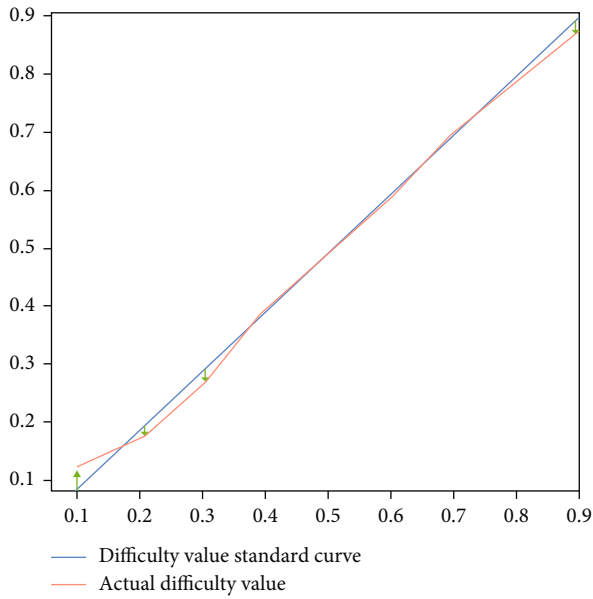
FIGURE 6: Comparison results of actual recommended exercise difficulty and theoretical difficulty index values of exercise recommendation model.
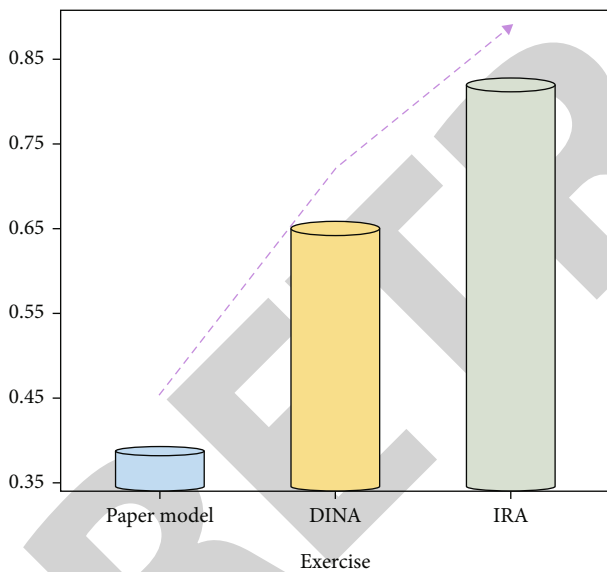

FIGURE 7: Comparison results of exercise list recommendation effects of three exercise recommendation models.

classified knowledge points in the above. The combination of the two can ensure learners' good practice experience, recommend targeted and systematic exercises, take care of all knowledge points, and promote learners' enthusiasm. According to the above, the result range is [0,1]. Set the upper and lower line of the accuracy value of the recommendation list within its range, that is, θ_1, θ_2, and the accuracy range of all the exercises to be recommended in the recommendation list G is $[\theta_1, \theta_2]$.

For the list Q of exercises to be recommended generated from classified knowledge points, the average value of

learners' understanding of knowledge points shall be obtained before obtaining the results. This is the threshold of recommended exercises. The calculation method is as follows:

$$\mu = \frac{\sum_{v=1}^{h} C_{av}}{h}. \tag{14}$$

The mastery level of all exercises in list Q is lower than the threshold. Compare these exercises with those in list G to be recommended, and obtain the exercises jointly owned by them and put them into the final exercise recommendation list, as shown in Figure 2. If there are no exercises jointly owned by the two, the exercises with the closest prediction accuracy to $[\theta_1, \theta_2]$ in all relevant exercises of the knowledge point will be included in the final list.

The advantages and disadvantages of the recommendation model are judged by the following indicators. The first is the prediction index of learners' score accuracy. The calculation method is shown in (17):

$$\text{Precison} = \frac{\text{FM}}{\text{RM}}. \tag{15}$$

Among them, the number of exercises whose predicted results are consistent with the actual results is FM, and the number of all recommended exercises is RM.

The difficulty degree of recommendation list of exercise recommendation model is calculated, as shown in the following formula:

$$\text{SR} = \frac{\text{TM}}{\text{RM}}. \tag{16}$$

Among them, the number of exercises that learners actually answered correctly is described by TM.

The calculation formula of recommended efficiency of exercises with full coverage of model knowledge points is shown in (17):

$$\text{MP} = \frac{\text{RM}}{\text{Total}}. \tag{17}$$

4. Experimental Results of Exercise Recommendation Algorithm Based on Cognitive Level and Data Mining

Previous recommendation systems focus on the optimization of recommendation performance, rarely can clearly reflect the learning state of learners' knowledge points, and there are large errors in the recommendation results. This paper combines the comprehensive cognitive analysis module with the classified knowledge point cognitive analysis module to analyze learners' cognitive degree of knowledge points. Based on the above excellent theory and practice, inherit and carry forward the previous research results. It is intended to introduce data mining methods into problem-solving solutions. So that it can scientifically guide
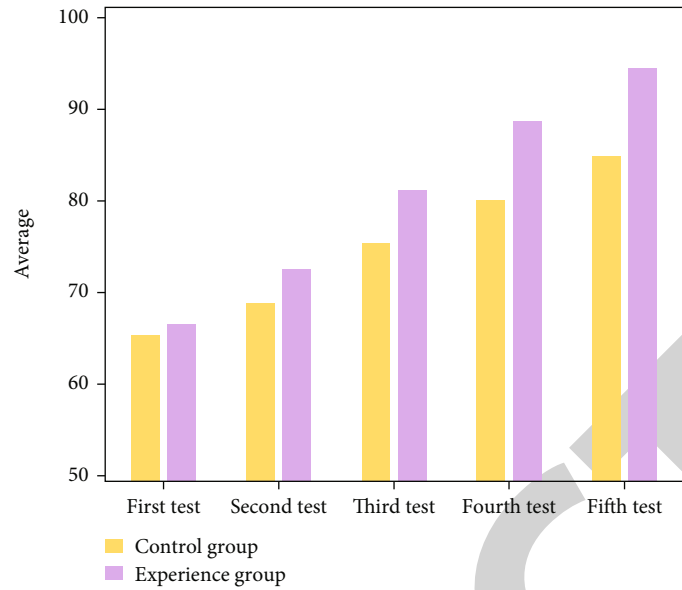
Figure 8: Comparison of average scores of five tests between experimental class and control class.
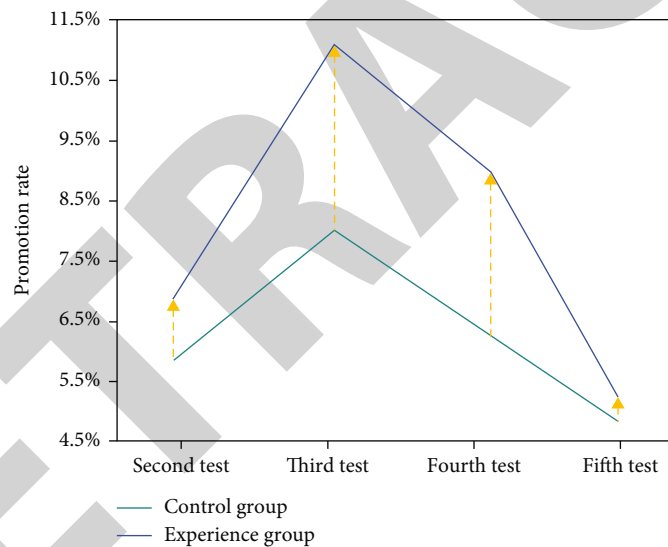

Figure 9: Comparison of the average score improvement rate of four tests between two classes.

students to arrange courses according to students' employment satisfaction and other factors.

In this paper, four data sets are selected for the recommended comparative experiment of mathematical exercises. Three data sets are open, but the scale of relevant data is small, and the amount of mathematical exercises is not enough to ensure the experimental effect. Therefore, the fourth data set is used to make up for it, as shown in Figure 3.

After the preliminary preparation for model training, call the fit interface to start the training process. You need to specify at least three key parameters: training data set, training rounds, and single training data batch size. The classification accuracy will still shake or fluctuate when the overall trend declines. If you stop when accuracy begins to

decline, you will definitely miss a better choice. So a good solution is to terminate when the classification accuracy is no longer improved within a certain period of time. Of course, it is OK to use loss in this area, and loss is also a criterion. The cognitive adjustment parameters in the exercise recommendation model have a regulatory effect on two cognitive degree modules, that is, in $\delta = 0$, the learners' cognitive degree of classified knowledge points determines the prediction results of accuracy, on the contrary, in $\delta = 1$, the learners' comprehensive cognitive degree plays a major decisive role. Figure 4 shows the result changes of exercise recommendation model of frcsub dataset under different parameter values. The overall data in the figure shows a state similar to the positive Pacific distribution, that is, the values on both sides are lower than the middle value. The higher

the value, the better the recommendation effect. Therefore, the performance of exercise recommendation only based on any learner's cognitive level is not good. The exercise recommendation results obtained by the combination of the two are higher than those in a single case, which shows that the combination of comprehensive cognition and the cognitive degree of classified knowledge points can better show the learners' actual cognitive state from multiple angles. In addition, in the case of single cognition, the cognitive degree of classified knowledge points is higher than that of comprehensive cognition. When the data performance is the best, the cognitive degree of classified knowledge points accounts for more proportion in the value of adjustment parameters, which shows that learners improve the cognitive degree of classified knowledge points, even if the granularity of knowledge points is smaller, so as to promote the accuracy of exercises.

The adjustment parameter of the model is $\delta = 0.35$. The recommended model, project reflection theoretical model, and classical discrete model are tested for exercise accuracy prediction in three open data sets. The comparison of the results is shown in Figure 5. Among the three models, the recommended model in this paper shows the best results, the gap between the results of the classical discrete model and the model in this paper is small, and the accuracy of the project reflection theoretical model is the least ideal. This shows that the proposed model is more accurate in reflecting learners' cognitive level. In addition, the size of the data set has a certain impact on the test results. The larger data set provides more effective data for the model, which is conducive to the model to obtain finer prediction results.

In practice, learners with different cognitive states need different exercise difficulties. The exercise recommendation model can select and recommend exercises within a certain difficulty range according to the middle value of different difficulty needs. Exercise recommendation model is used to describe the internal and external learning characteristics of learners, and it is the premise and foundation of learning analysis. Practice recommendation model is of great value to teachers, learners, and learning system managers. Whether the various characteristics of learners contained in the practice recommendation model are complete and accurate is related to whether teachers can classify learners with similar learning characteristics according to the model and then provide students with personalized learning content, strategies, and learning resources. In addition, the practice recommendation model is conducive to learners' in-depth understanding of their learning status and shortcomings and then correct their learning behavior in advance.

Figure 6 shows the comparison results of the actual recommended exercise difficulty and theoretical difficulty index values of the exercise recommendation model. The data in the figure shows that the recommended difficulty of practical exercises is basically consistent with the theoretical difficulty on the whole, and there is only a small error at both ends, that is, when the difficulty of exercises is in the range of high or low, the actual difficulty of exercises will have a certain deviation, which is mainly because the coverage of model compromise processing knowledge points has an impact on the actual presentation of exercise difficulty. On the whole, this model can recommend a list of exercises with appropriate difficulty according to learners' actual needs and cognitive state.

As shown in Figure 7, the comparison results of exercise list recommendation effects of three exercise recommendation models are shown. The recommendation efficiency of exercises with full knowledge coverage is taken as the test index. The larger the value of this index, the worse its efficiency is. At this time, the difficulty coefficient is uniformly set to 0.55. In order to ensure the accuracy and effectiveness of the experimental results, this part of the experiment is carried out in the fourth data set with large data scale. The results show that the index value of this model is the smallest, that is, the recommendation efficiency is the highest, and the gap between the index values is relatively large compared with the other two models, indicating that the efficiency of this model has been greatly improved. Therefore, the model design in this paper has a good effect on the coverage of knowledge points and abnormal data processing and can ensure a good effect of exercise recommendation.

In this paper, two classes with the same number and academic achievements in a middle school are selected for the comparative experiment of the application of exercise recommendation model. One class is the control class, which adopts the traditional educational exercise practice method, and the other is the experimental class, which adopts the exercise recommendation model practice in this paper. There are five performance tests during the comparative experiment. The first is the preexperiment test. The results are shown in Figure 8. The test results before the experiment show that the average score gap between the two classes is very small, and the average score keeps increasing during the experiment. In the subsequent tests, the average scores of the experimental class are higher than those of the control class. This shows that the exercises in traditional teaching are helpful to improve learners' performance. The exercises recommended by the exercise recommendation model are more targeted and perform better in improving learning efficiency and test performance.

As shown in Figure 9, the results of the improvement rate of the average score of the four tests of the two classes are compared. The improvement rate of the average score of the four tests of the experimental class is higher than that of the control class. The improvement rates of the second and last tests of the two classes are relatively low, mainly because of the low mastery and application ability in the primary stage of learning knowledge points. In the fifth test, the learning knowledge points have entered the optimization period. In this stage, the score improvement difficulty is high, and the promotion rate is reduced. In the third and fourth tests, the promotion rate of the experimental class is significantly higher than that of the control class, which shows that in the knowledge point foundation consolidation and application stage, the exercise recommendation algorithm based on cognitive level and data mining meets the needs of learners in different stages and strengthens the practice of learners' knowledge points in a targeted and personalized manner in a short time to quickly improve learning efficiency.

5. Conclusion

This paper establishes an analysis model of learners' cognitive level of knowledge points, selects appropriate exercises according to the analysis results, and forms a recommendation list. According to the teaching comparison experiment, in the practical application of the recommended exercises, the exercise recommendation system meets the personalized needs of learners, maintains good accuracy, effectively helps learners lay a solid foundation, improves learning efficiency and effect, and greatly improves examination performance. In order to comprehensively analyze learners' cognitive state from multiple perspectives, the cognitive model includes a comprehensive cognitive analysis module and a cognitive degree analysis module of classifying knowledge points. The problem recommendation algorithm based on cognitive level and data mining proposed in this paper needs further systematic improvement and research on the impact of time factors on learners and the connection factors between knowledge points. The experimental results show that when the motion recommendation algorithm based on cognitive level and data mining has the best recommendation effect, the cognitive module of classifying knowledge points accounts for a large proportion in adjusting parameters. Compared with other recommendation systems, this model has higher accuracy and recommendation effect.

However, it is difficult to obtain fine-grained recommendation data information from the interaction between users and exercise information in this study, so the accuracy of exercise recommendation results needs to be improved. This needs to be analyzed in future research.

Data Availability

The data 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 known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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