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Retraction

Retracted: Research on Learner Modeling and Curriculum Recommendation Based on Emotional Factors

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Manipulated or compromised peer review

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] X. Hua, H. Zhang, F. Xie, J. Wei, J. Wei, and H. Li, "Research on Learner Modeling and Curriculum Recommendation Based on Emotional Factors," *Journal of Sensors*, vol. 2022, Article ID 3296713, 9 pages, 2022.

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Research Article

Research on Learner Modeling and Curriculum Recommendation Based on Emotional Factors

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With the increasing with the number of courses, learners cannot find the courses they need quickly. Therefore, the primary problem to change the efficiency of online courses is to recommend corresponding courses for a certain group of people according to their needs. Learner characteristics are an important aspect of reflecting learner preferences, and learner models are abstract representations and descriptions of learner characteristics. It is necessary to enhance the use of online courses among students; we must build a relatively comprehensive curriculum model. At present, the construction of learner model is mostly based on cognitive level and learning style, ignoring the emotion expressed by learners to the curriculum, and emotion is a very important characteristic of learners. In order to establish a perfect learner model, it is necessary to incorporate learners' aspect emotion into the learner model to make the course recommendation process more accurate. Firstly, based on the attention mechanism long-term and short-term memory network, this paper extracts the learner's aspect emotion to the curriculum from the learner's curriculum review. At the same time, it studies various characteristics, such as demography, cognitive level, motor behavior, and learning style. By establishing a perfect model integrating researchers' emotional state, finally, the complex interaction between learner characteristics and curriculum characteristics is modeled by using deep factor natural decomposition, so as to achieve accurate curriculum recommendation. In this study, the learner's aspect emotion is included in the construction of learner model and enriched and perfected the learner model. It provides a reference for the theoretical research and applied research of learner model and has reference significance. At the same time, combining Deep learning can improve the accuracy of course recommendation, help learners' learning efficiency and personalized learning quality, and also contribute to the long-term development of online platform. The mathematical modeling in this paper uses learning analysis technology and general factor model based on matrix factorization to calculate and uses factorization machine to reduce the dimension of high-dimensional data, which is efficient and accurate.

1. Introduction

The influence of emotional factors on people lies in many aspects. For example, emotional factors play a role in attitude, which is a comprehensive evaluation of people's self, others, problems, abstract concepts, and other objects. For example, if a person likes ice cream, emotional factors affect a person's attitude. Similarly, influenced by personal emotional factors in modeling, learners will build their own favorite style [1]. A study of German students' learning process shows that emotional factors have a great influence on learning, positive emotions are more important in students' learning stage than in practice stage, and anxiety plays an ambiguous role in learning practice stage; in addition, the fun and interest of learning is particularly important in the learning process [2]. This paper compiles an emotional dictionary based on basic emotional words and phrases. With punctuation marks and emoticons, a set of emotional rules is established, and a set of algorithms based on emotional rules and dictionaries is summarized. Experimental results show that the algorithm is effective [3]. Studies have shown that a dedicated pathway assesses the threat relevance of visual input, leading to priority acquisition of awareness of threat stimuli. Fearful faces are easier to get rid of depressed emotions; low-level faces and consciousness are not determined by emotional factors [4]. In this paper, Rorschach ink method and diagnostic interview form were used to explore the relationship between emotional factors and subjective quality of life of subjects with spinal cord injury. By comparison, the results show that the subjects with spinal cord injury are satisfied with the assessment of the overall subjective quality of life, but there are still some unsatisfactory places, which become the source of mental pain [5]. The observation results of this paper show that the total precipitation in many areas is amplified at the tail, which makes the social infrastructure more sensitive to extreme weather and climate, and extreme climate change will aggravate this situation. This extreme weather will affect the field modeling [6]. Homeostasis model evaluation is a method to evaluate beta cell function and drug resistance from baseline (fasting) and C concentration. The model was described by an approximate estimation formula in 1985 and has been verified by various physiological methods. When used, it can produce valuable data. Hybrid modeling is a data analysis technique used to identify unobserved heterogeneity in a population. Among the tests and indicators of potential class analysis, factor mixed model, and growth mixed model, Bayesian information criterion performs best in ICS, but bootsrap is still proved to be an indicator of very consistent test indicators in all models [7]. Agent modeling is a powerful simulation modeling technology, which has four application fields: flow simulation, organization simulation, market simulation, and diffusion simulation [8]. Polynomial is a discrete selection model, which is widely used in the modeling of ranking data. A scalable approach to approximate polynomials has been developed, which is suitable for selection-based network modeling [9]. Curriculum recommendation system has been proposed as a tool to help students make wise curriculum choices. A course recommendation system, which combines the data mining process with user rating in the recommendation process, provides users with the possibility of rating. RARE combines the experience of previous students with the scores of current students to recommend the most relevant courses to users [10]. Curriculum recommendation system plays an important role in managing curriculum and guiding students' studies, so as to promote students' academic progress. Previous systems were not perfect, and the hardware devices were not up to standard, so these systems were not based on industry standards. With the development of science and technology, mobile phones have become a typical terminal for learning, and many course recommendation systems have appeared. This paper introduces a mobile course recommendation system, which can help students choose and access the courses required by their professional fields. The system can assist the course coordinator in tutoring students [11]. Recommendation system is widely used in many Internet activities. This paper discusses the ability of recommendation system to support students' needs in learning management system or curriculum management system and designs a suggestion structure of learning management system, which can recommend courses for students [12]. This study uses ontology technology to realize course recommendation, provide students with adaptive learning recommendation, and let students reserve the knowledge they need to enter the workplace in the future [13]. Course selection is an important part of students' development, and a good learning strategy can be obtained from course recommendation methods. In this study, we propose a deep learning technology, multilayer perceptron, and preprocessing method of course recommendation system. The results show that these predictions have good results for students to provide suggestions for course selection and are expected to be applied in practical application [14].

2. Concepts Related to Learner Model

2.1. The Meaning of the Learner. The meaning of learner is a person who participates in social teaching activities. As its concept expands its scope, its characteristics begin to appear, such as consciousness, autonomy, and creativity. Under the condition of learning, learners can get more opportunities for plasticity and sustainable development. From other people's point of view, his goal is very clear, and then their attitude changes from passive to active. And then it has greater demand for its own development and richer connotation.

These changes also cause changes in characteristics. In traditional pedagogy, the characteristics of learners are very simple, including demographic characteristics. Nowadays, the characteristics of learners are very rich, including educational background, emotional attitude, goals, and family background. Learner characteristics play an important role in curriculum system design, instructional design, personalized learning resource recommendation, and other fields and are widely used. At present, people are keen to analyze the characteristics of learners to make accurate portraits of learners, so as to provide various learning services for personalized learning.

2.2. Learner Emotion. The various emotional states produced in the learning process are learners' emotion, which is a very important feature and can accurately express learners' learning hobbies. When the learner is in a positive mood, he likes this kind of course. Therefore, if we can find this positive emotion, we can describe the learners' hobbies more accurately, provide them with more perfect learning services, and improve learning efficiency. Usually, we can get the information of learners' hobbies through emotion mining in text comments, questions, and forum interactions.

2.3. Learner Model. With the rise of information technology, online courses have also increased, and the traditional education mode has changed. Learning is no longer limited to school classrooms. More and more people are learning on different learning platforms, leaving a large amount of learning data, which lays a foundation for providing personalized learning support services. Learner model appears with the

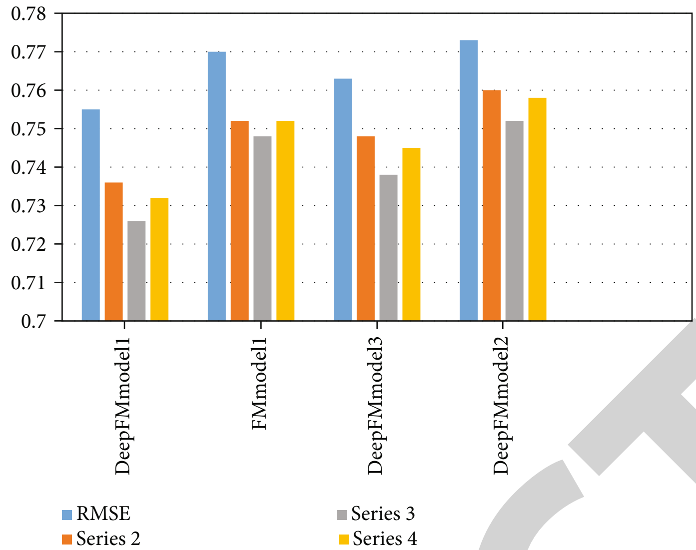

Figure 1: RMSE value of each model with the increase of iteration times.

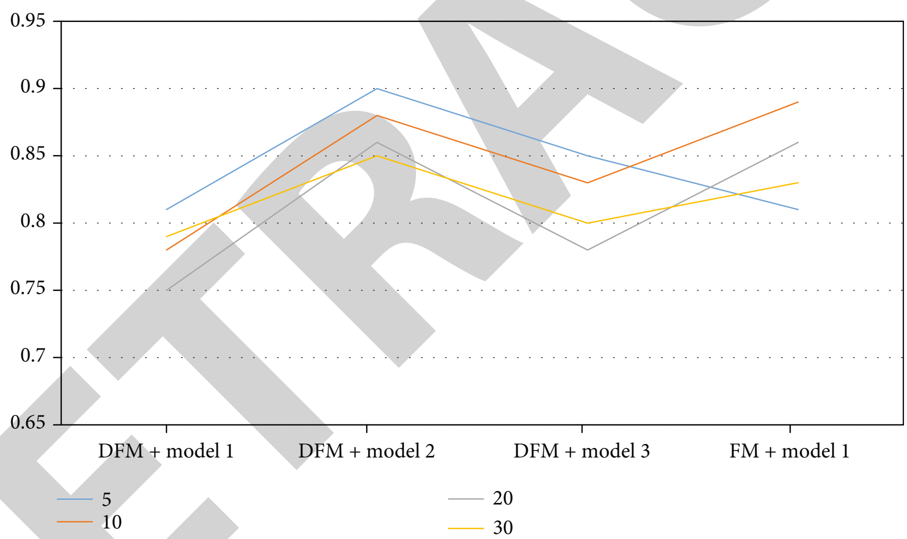

Figure 2: Comparison of MAE values of various models.

Table 1: MAE values of each model with the increase of iteration times.

Iteration times	DFM + Model 1	DFM + Model 2	DFM + Model 3	FM + Model 1
5	0.81	0.90	0.85	0.87
10	0.78	0.88	0.83	0.85
20	0.75	0.86	0.78	0.82
30	0.79	0.85	0.80	0.81

emergence of intelligent teaching system; it is an abstract representation and description of learners' characteristics. Its core elements are learner information and learner characteristics. It is a mathematical model mainly including learners' cognitive level, emotional attitude, learning style, and demographic information, and it is an important component of personalized learning support service system.

3. Related Learner Modeling Techniques

3.1. Learning Analysis Techniques. Facing the huge and complicated educational data, however, the previous statistical calculation methods cannot deal with data sets with different properties, and the computational complexity will increase with the increase of the number of features, the processing effect for high-dimensional sparse data is poor, and the data analysis cannot achieve the expected effect. Under the support of statistics, artificial intelligence, machine learning, and other fields, learning analysis technology came into being. Learning

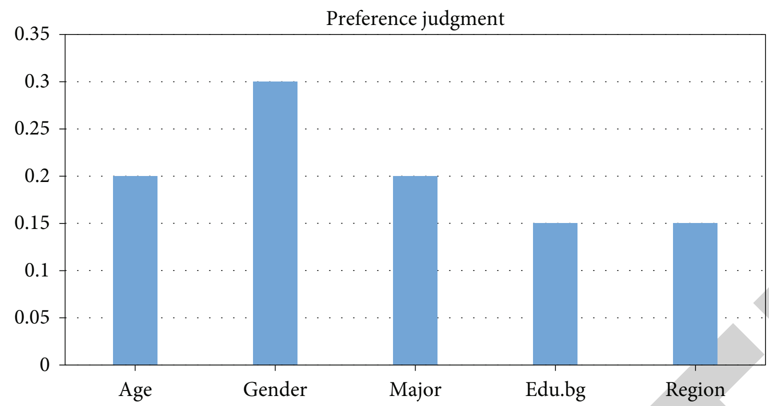

Figure 3: Influence degree of various factors on user preference.

analysis technology refers to the use of educational data mining implicit information that can reflect learning preferences to build a model, so as to predict learners' learning situation, so as to make benign intervention on learning or provide learning support services for learners. It is a decision-making aid tool. Learning analysis technology helps teachers to better understand learners, optimize teaching, and help learners learn independently and individually. In recent years, learning analysis technology is widely used in various fields of education, and it is becoming more and more common.

3.2. Factorize. Factorization machine is a commonly used decomposition model. Compared with the traditional factorization model, the factorization machine has unlimited number of features, strong expansibility, as well as the fickle characteristic change pattern; it can not only deal with complex data well, but also deal with high-dimensional data well.

For an n-dimensional eigenvector x, $X=(x_1, x_2 \cdots x_n) \in R^n$, where $x_1, x_2 \cdots x_n$ is not independent of each other and y_i is the predicted value of the corresponding target. When $n=2$, the expression is

$$y(x) = w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} < v_i, v_j > x_i x_j, \tag{1}$$

where $w_0 \in R, w \in R^n, x_i x_j$ represents the interaction of eigenvectors x_i and x_j and the coefficient matrix, $V \in R^{n\times k}$, $<v_i, v_j>$, is the dot product of vectors v_i and v_j of size K, and the expression is

$$<v_i, v_j> = \sum_{f=1}^{k} v_{i,f} \cdot v_{j,f}, \tag{2}$$

where $k \in N^+$ is the hyperparameter that defines the decomposition dimension and $v_{i,j}, v_{j,f}$ is the hidden factor of the hidden vector corresponding to the feature vectors x_i and x_j, respectively.

The factorizer can decompose the transformation between a large value and a small function and then use the product of$v_i$and$v_j$for predictive modeling, which can effectively alleviate the problems caused by sparse data and improve the efficiency of recommendation.

Table 2: Statistical basic data of general characteristics of users.

Number of users	Number of courses	Number of features
2311	124	6

3.3. Deep Learning. RNN can hold internal information, so it can accurately predict the next information according to the previous input information, especially in the in-depth understanding of context, and plays a huge role. Hochreiter and Schmidhuber proposed a memory network at any time. In the LSTM structure, there are three gates: forget gate, input gate and output gate, and memory status. Red represents bitwise operation of elements, yellow represents neural network layer, and the arrow indicates the cell state, where the information is stable. There are two parts here: First, the input gate layer determines what value we will update; then, a tanh layer creates a new candidate value vector, which is added to the state. Next, the cell state is updated, and finally the output gate determines the information to be output based on the cell state. For example,

$$f_i = \sigma\left(w_f[x_i, h_{i-1}] + b_f\right). \tag{3}$$

Formula (3) is the formula of forgetting gate, and its content is x_i and h_{i-1} and outputs the value of each number in the cell C_{i-1}. 1 means "completely retained," and 0 means "completely discarded."

In Formulas (4) and (5), C represents the vector of new values, and I_i determines what value is updated:

$$I_i = \sigma(w_I[x_i, h_{i-1}] + b_I), \tag{4}$$

$$C = \tanh\left(W_c[x_i, h_{i-1}] + bc\right), \tag{5}$$

$$C_i = f_i^* C_{i-1} + I_i^* C_i. \tag{6}$$

Formula (6) indicates that an individual's emotional state changes fromC_{i-1}toC_i, $f_i^* C_{i-1}$, means to discard the information determined to be discarded in the previous step,

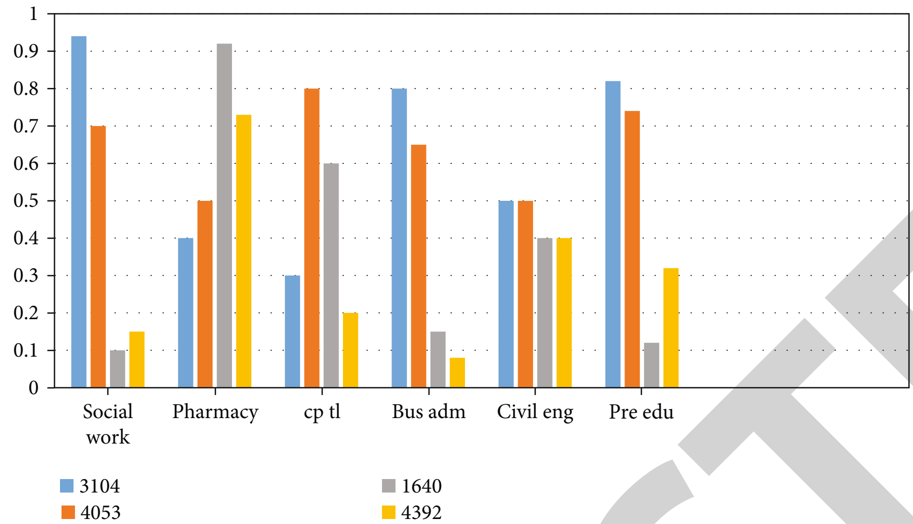

FIGURE 4: Distribution of elective courses for students of different majors.

which is the new candidate value vector

$$o_i = \sigma(W_0[x_i, h_{i-1}] + b_0), \quad (7)$$

$$h_i = o_i^* \tanh(C_i). \quad (8)$$

Equation (7) represents the state to be outputted and then is processed by Equation (8) to obtain a value between -1 and 1 and determine the part to be outputted.

3.4. Long-term and Short-term Memory Networks Based on Attention Mechanism. Standard memory neural networks cannot distinguish emotions in sentences. The attention mechanism in deep learning is similar to the selective attention mechanism of human beings. When different emotions appear, we can grasp the important parts of sentences. The ultimate goal is to select the information that is more critical to the current goal from the information and ignore the irrelevant information. Therefore, the attention mechanism can also reduce the computation of deep learning, which is the shortcoming of LSTM neural network. In order to solve this problem, Ren et al. proposed a variant of LSTM, that is, by introducing attention mechanism, a long-term and short-term memory network based on attention mechanism was proposed, which can capture key parts of sentences to respond to given aspects. The mathematical expressions are shown below:

$$M = \tanh\left(\begin{bmatrix} W_h H \\ W_v v_a \otimes e_N \end{bmatrix}\right), \quad (9)$$

$$\alpha = soft\max\left(w^T M\right), \quad (10)$$

$$r = H\alpha^T, \quad (11)$$

$$h^* = \tanh\left(W_{p^r} + W_x h_N\right). \quad (12)$$

where $M \in R^{(d+d_a)*N}$, N represents the sequence length of the sentence, H represents the hidden node of the input sentence, Formula (12) is the final prediction formula, W_{p^r} and W_x are the parameters to be learned in the model, h^* represents the sentence feature representation of the given input aspect, and h_N represents the hidden vector of the last layer of the hidden layer.

3.5. Deep Neurofactorization Machine. The factorization machine (FM) can reduce the dimension of high-dimensional data, but it can only model the low-order data linearly, while neural network can model the high-order data nonlinearly, but the parameter estimation will be very complicated when the data is sparse. In view of this, Guo and others put forward the Deep Neurofactorization Machine (DeepFM). DeepFM combines FM with DNN that can simulate both low-order feature interaction and high-order feature interaction, and DeepFM can carry out end-to-end training without any feature engineering. Its training mode is as follows:

$$y = \text{sign}\, moid(y_{FM} + y_{DNN}), \quad (13)$$

where y_{FM} is the output of FM component, y_{DNN} is the output of Deep component, and y∈ (0, 1) is the prediction result of DeepFM. The expression for Va is as follows:

$$y_{FM} = \langle w, x \rangle + \sum_{i=1}^{d} \sum_{j=i+1}^{d} \langle V_i, V_j \rangle x_i \cdot x_j, \quad (14)$$

where$\langle w, x \rangle$represents the first-order feature, the inner product represents the second-order cross feature, and the expression of$y_{DNN}$is shown below:

$$a^{(l+1)} = \sigma\left(w^{(l)} a^{(l)} + b^{(l)}\right), \quad (15)$$

$$y_{DNN} = W^{|H|+1} \cdot a^{|H|} + b^{|H|+1}, \quad (16)$$

where σ represents the activation function, l is the number of layers of DNN, $w^{(l)}$ represents the weight of DFM, $a^{(l)}$ represents the output of layer l, $b^{(l)}$ is the bias term, and $|H|$

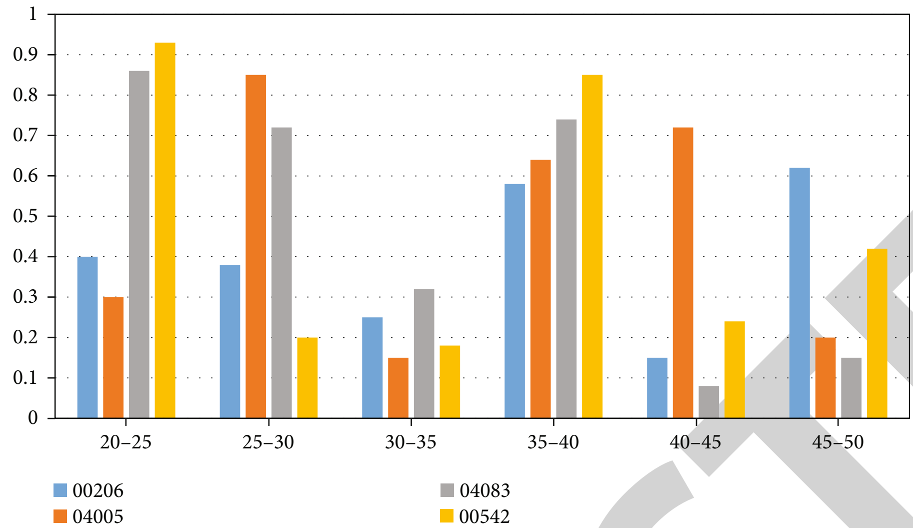

FIGURE 5: Distribution of elective courses of students of different ages.

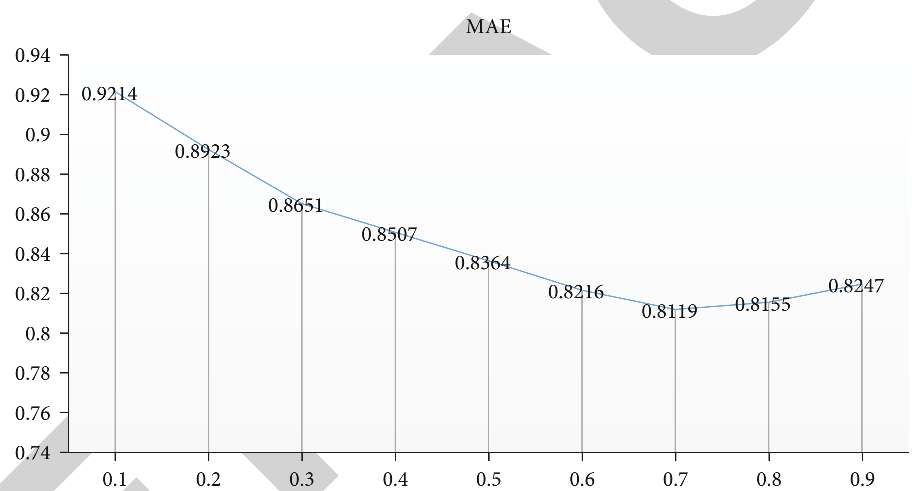

FIGURE 6: Effect of different μ values on MAE.

TABLE 3: Variation of MAE value with user's professional weight.

$\mu 1$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
MAE	0.9214	0.8923	0.8651	0.8507	0.8364	0.8216	0.8119	0.8155	0.8247

represents the number of hidden layers. After Formula (15) is completed, a predicted value is generated. The so-called activation function is a function running on the neurons of artificial neural network, which is responsible for mapping the input of neurons to the output.

The data of depth neurofactors are input from deep to hidden places. If you report an error, the parameters will be adjusted to the allowable error range and then output through the output layer of the hidden layer. Different levels will be constantly adjusted, and the parameters will be trained in this mode, so as to complete the learning of the data by the model. Average loss function can improve the efficiency of the model:

$$L_{reg} = \sum_{x \in D} \left(r'_{u,i}(x) - r_{u,i}(x) \right)^2, \tag{17}$$

where D represents the training set and $r_{u,i}(x)$ is the user's satisfaction score with Series I.

3.6. Input Vector Representation of Decomposer. Feature recommendation has the greatest influence after use. On the basis of the established researcher function, the study describes this method from many aspects. Popular courses are determined by course scores, course participants, and score participants.

The formula is shown below:

$$Popularity(i) = AS_i * NP_i / CP_i, \quad (18)$$

where $Popularig\ (i)$ represents the popularity of the first course, AS_i represents the average score of the first course, NP_i represents the number of people who participated in the scoring, and CP_i represents the number of people who signed up for the course.

Prediction accuracy is the most commonly used evaluation index in recommendation field. RMSE represents the sum of squares of the deviations of two values and the square root of the data set m, calculated by

$$RMSE(x, h) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(h\left(x^{(i)}\right) - y^{(i)}\right)^2}. \quad (19)$$

MAE is calculated by

$$MAE(x, h) = \frac{1}{m}\sum_{i=1}^{m}\left|h\left(x^{(i)}\right) - y^{(i)}\right|. \quad (20)$$

The data obtained are more accurate when the root mean square error and absolute error values are small. In the field of information retrieval and statistics, accuracy and recall are measures and indicators to check experimental performance, which have been widely used. The calculation formulas of accuracy and recall rate are as follows:

$$Precision = \frac{TP}{TP + FP}, \quad (21)$$

$$Recall = \frac{TP}{TP + FN}. \quad (22)$$

Precision refers to the proportion of items that users are interested in recommended by the recommendation system in all recommendation lists. The higher the accuracy, the better the performance and better the effect of the algorithm. Recall refers to the proportion of the correct items recommended by the recommendation system in all the items that users are interested in. Similarly, the larger the ratio, the higher the coverage rate and the better the effect.

Prediction accuracy is the most widely used evaluation index in the recommended field as defined below:

$$MAE = \frac{\sum_{n=1}^{N}|pi - qi|}{N}, \quad (23)$$

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N}(pi - qi)^2}{N}}, \quad (24)$$

where $\{pl, p2 \cdots pn\}$ is the user rating set predicted by the recommendation algorithm and $\{q1, q2 \cdots qn\}$ is the actual user rating set. The smaller the RMSE and MAE, the smaller the error between the predicted user score and the actual user score, and the higher the recommendation quality; on the contrary, it shows the lower the recommendation quality.

4. Comparative Experimental Selection

4.1. Selection of Curriculum Recommendation Indicators. In order to verify the feasibility of the proposed model, the learner model with emotion (Model 1), the learner model without emotion (Model 2), and the learner model with learner emotion (Model 3) are applied course recommendations to compare the advantages and disadvantages of the three methods. The experimental steps are divided into three steps:

(1) DeepFM is used to recommend courses based on courses: In the absence of an emotional state, this model can accurately reflect learners' learning hobbies

(2) Based on Model 3, DeepM is used for course recommendation: Being able to tell by integrating learners' aspect motion can reflect learner preference than simply integrating learners' whole emotion

(3) The course recommendation based on FM model 1 is based on the classical FM, and the traditional recommendation technology can also achieve good results in judging the learner model, while the recommendation accuracy of the deep learning technology is higher than that of the general FM

4.2. Experimental Data Analysis. Figure 1 is the root mean square error values recommended by Models 1, 2, and 3 that is calculated and counted using a factorizer, and the error Model 1-based data values use the traditional values' recommendation course. It is shown from the figure that with the increase of iteration times, the error value is constantly changing. When the number of times is 30, the error values when the accuracy is the highest, DFM and FM, are the lowest, so as to achieve the best state. The error value of DFM is the lowest in Model 1, followed by DFM recommendation based on Model 3, and finally DFM course recommendation based on Figure 2.

The comparison of MAE values of each model in Figure 2 shows that when the iteration times are 30, the sum of absolute values of the difference between the target value and the predicted value of Model 2 recommended by DeepFM is the largest; Model 3 recommended by DeepFM is the smallest.

The number of iterations in Table 1 refers to the gradual increase in the number of course recommendations for various models.

Table 1 shows the values calculated using a neural factorize, the RMS error values for the courses recommended by Model 1, Model 2, and Model 3, and the average of the absolute errors recommended by Model 1 using traditional FM recommendations. The data shows that when the number is 20, anyone of the course recommendation model is used, and which decomposition technology is based on, the average recommendation value of Model 1 is the smallest, and

DFM based on the same learning recommendation model has better performance and other aspects than FM.

4.3. Predictive Score Based on Statistical User Characteristics. At first, in the course recommendation system, the course recommendation algorithm often lacks considering the influence of user attributes on the results. Recommendation performance for new users is poor, but in practical application scenarios, the user feature attributes also affect recommendation accuracy. The users with the same attributes have similar preferences for courses. The distribution of users on different features is counted, and the factors that have great influence on the popularization of curriculum application are found. The weighted summation of the features is used to obtain the prediction score based on the statistical user characteristics.

Figure 3 shows that the common characteristics of users usually include the following: age, gender, major, occupation, region, educational background, and income. Usually these attributes will affect the judgment of users' preferences. Analyzing Figure 3, gender has the greatest influence on the judgment of user preference. Secondly, age and major, educational background and region, income, occupation, and so on have little influence on user preference judgment.

Through the statistical analysis of the data in Table 2 on the characteristics of users' age, gender, major, occupation, region, and educational background, the two characteristics with the largest gap in the number of students who choose the same course under different user characteristics are selected as the most important factors affecting the recommendation results. The statistical results are shown in Figures 4 and 5, and it is found that the major and age of users have the greatest influence on the course recommendation results.

However, a course may become a popular course because of its short class hours or kind attitude of teachers so that the F value calculated by any user will be very large and popular courses are largely recommended to target users. However, the courses that users choose less become unpopular courses, but these courses will also be helpful to different users. Therefore, the attenuation factor is introduced to give less weight to popular courses, thus reducing its influence on recommendation results.

The ordinate in Figure 6 represents the effect of different μ values on the sum of the absolute values of the difference between the target value and the predicted value.

In order to further determine the importance of user's specialty and age on course recommendation, the user's specialty weight μ is set between 0 and 1, and the value m which is beneficial to give the best recommendation result is found according to the average absolute error of users with different characteristics. According to the curve trend in Figure 6 and the average absolute error of user's professional characteristics in Table 3, it can be seen that the best recommendation result can be obtained when the weights of user's professional and age are 0.7 and 0.3, respectively.

According to the above analysis, we can draw a conclusion that whether using DFM or FM for personalized curriculum recommendation, Model 1 has the highest accuracy in the field of curriculum recommendation, and on the basis of Model 3, the accuracy of DFM curriculum recommendation is higher than other models. All this shows that the emotional state characteristics of learners play a key role in improving the accuracy of curriculum recommendation. In this study, the fusion of emotional factors is to build a model to improve and make up for the general model of emotional state deficiencies.

5. Conclusion

In this paper, emotional factors are integrated into the model and applied to online courses in colleges and universities and recommendation in universities after integrating emotional factors, and the personalized and accurate course recommendation for learners is realized by using matrix neural factorization. And then, after setting up the experimental group and comparing it, the experiment shows that the model of curriculum recommendation with affective factors has less error and better effect, while the learner model without emotional factors has higher recommendation accuracy, and the learner model with emotional factors has higher recommendation accuracy. Under the same model, DFM has higher accuracy than FM. This shows that the modeling calculated in this article is very useful and that whether learner's attitude is positive or not is the key to accurately describe the learning preference, as well as the advantages of learning recommendation technology applied to courses in various aspects. This study provides a reference for the study of learner model from the theoretical inquiry level to the practical application level.

Although this study has realized the application of learner model, it is not deep enough in the application field, only using deep learning technology to make recommendation, and lacks in-depth research on recommendation methods. In order to obtain higher recommendation accuracy, it is necessary to conduct in-depth research on recommendation methods based on learner model in the later stage.

Data Availability

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

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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