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Analysis of Teachers' Self-Improvement and Development Paths Based on Artificial Intelligence Technology

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SUMMARY: *This paper designs and proposes a constructive recommendation model framework composed of knowledge network module and constructive recommendation module, adding constructivist recommendation strategy to form a personalized knowledge recommendation model based on constructivist learning theory. Improve the insufficiency of matrix decomposition, design the user feature generation, information matching and generating recommendation three parts to constitute the big data recommendation module. Design the teaching quality assessment module and apply it to the assessment of teachers' self-improvement ability development level. Taking the practice course as an example, we analyze the accuracy of the personalized knowledge recommendation model based on constructivist learning theory in recommending learning resources during teachers' online learning process. Based on the evaluation results of the teaching quality assessment module, we found that there are significant differences in the self-improvement practice dimensions among teachers of different age groups. The scores of self-improvement awareness dimension, learning dimension, and practice dimension are good. The overall assessment result of teachers' self-improvement is 77.54, which is a good overall level. Teaching practice using personalized intelligent knowledge recommendation model can assist teachers' self-improvement and can be used as one of the paths for teachers' professional development.*

KEYWORDS: *personalized knowledge recommendation; matrix decomposition; teaching quality assessment; learning resources; teacher self-improvement*

1 Introduction

In the context of education reform, teachers' self-improvement has become the core of improving education quality and a key factor in promoting the forward development of education [1, 2]. However, in the digital era, the social environment is complex, changeable, and possesses infectious nature, the knowledge learning path is rich, and the intelligent teaching tools are widely applied, which makes teachers, a group that is assigned with very high social role expectations, face great threats [3-5]. Literature [6] points out that teachers should actively participate in academic seminars and publish papers to improve their own research skills and teaching level, so as to increase students' interest in learning and satisfaction, and continuously

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realize self-improvement with the concept of lifelong learning. Teachers need to start a new journey of self-improvement from the multiple dimensions of innovation of educational concepts, refinement of professionalism, innovation of teaching methods, and reform of the teaching evaluation system, to continuously improve their professional knowledge and skills, to strengthen their innovative thinking and abilities, and to learn digital technologies and tools for self-development [7-11]. Literature [12] constructed a model of teachers' information literacy self-improvement ability, analyzed the impact of new technology development on teachers' self-improvement, and revealed that teachers' self-improvement in information literacy is currently insufficient and is affected by factors such as gender, age, school, educational experience, and geography. It is essential to find the entry point for teachers to realize self-improvement and development at the present time.

Artificial Intelligence (AI) can help teachers to deeply analyze the knowledge vein of the subjects they teach, and continuously update and enrich their own knowledge base, so as to make teaching more systematic and scientific [13, 14]. AI technology is deeply engaged in the three dimensions of education and teaching innovation, professionalism enhancement, and scientific evaluation system, which can further stimulate teachers' continuous self-improvement and professional development. Literature [15] points out that teachers' curriculum planning through AI generates curriculum standards and course content that meet the syllabus, optimizes the lesson preparation process and classroom task design, significantly improves teaching efficiency and teaching effectiveness, and saves teaching planning time while promoting their own digital literacy improvement. Literature [16] developed an adaptive training system for future teachers based on AI elements to help teachers pay attention to the development of the industry, as well as the updating of teaching experiments and teaching methods, and to improve the self-adaptive ability of future teachers to enter the education industry. Literature [17] suggests developing training paths for teachers' professional development with the help of AI technology, providing them with a full range of human resource services and training resource data, and creating a database in a global environment to promote teachers' professional development. Literature [18] survey shows that students and teachers in the AI-assisted education platform believe that the platform provides more possibilities for both parties, and functional modules such as assessment, personalized learning, learning analytics, lectures, etc. make students and teachers free from time and space constraints, and the response time for teaching and research is dramatically shortened.

In addition, literature [19] points out that AI technology can optimize the distribution of educational resources, narrow the digital divide of teachers, drive two-way interaction between urban and rural teachers, and promote the integration and development of urban and rural teachers, and the fairness of AI enables the construction of rural teachers in the long run. Literature [20] argues that teaching and learning involved in AI technology effectively promotes teachers' professional development, promotes teachers' confidence by optimizing teaching efficiency and critical thinking development, and assists teachers in providing personalized guidance and feedback to students, improving the effectiveness of teacher-student interaction. Literature [21] emphasizes that AI is only used as an auxiliary tool in the field of teaching, but the fair mechanism of AI-generated content makes AI-empowered teachers' self-professionalism enhancement effective and supported by teachers. However, the ethical and privacy risks associated with AI technology require the establishment of relevant traceability mechanisms to avoid the misuse of AI technology by teachers. Moreover, due to geographical differences, teachers' preferences for technology are also differentiated, so the development paths of teachers are also differentiated, and how AI technology can cope with this differentiation is a challenge nowadays.

In this paper, we point out the three major computational steps of Item-based CF algorithm

and its data sparsity and cold-start problems, and matrix decomposition suffers from the defects of high memory requirement and high computation in intelligent recommendation platform. Combining the constructive recommendation model framework with the constructivist recommendation strategy, a personalized knowledge recommendation model based on constructivist learning theory is proposed. The overall framework of personalized intelligent recommendation system for teachers' self-improvement of teaching skills is constructed, and the personalized intelligent recommendation module and teaching quality assessment module are planned. Introduce multiple models to compare the model evaluation results. Taking online course learning as an example, we analyze the recommendation AUC and ACC of the personalized knowledge recommendation model based on constructivist learning theory, carry out teaching practice, and measure the self-improvement development level of professional teachers based on the teaching quality assessment module.

2 Key technologies

2.1 Personalized Recommendation Technology

From the perspective of mobile Internet applications, user preference characteristics can be understood as the result of the user's subconscious life habits, attention to information, and operational processes reacted on the APP on mobile terminal. Users will browse, like, comment, collect, share and other operations when they use APP on mobile terminal to view resource information.

Personalized recommendation, on the other hand, collects these operation data through background technology and extracts effective data from them to establish a model to be analyzed, so as to understand the user's preferences and recommend more resource information that meets their interests and needs [22, 23].

Knowledge-based recommendation algorithms: there are two basic types of knowledge-based recommender systems, one is constraint-based recommendation and the other is instance-based recommendation. The former can be summarized as solving the constraint satisfaction problem with a constraint solver, while the latter mainly uses similarity measures to retrieve resource content from a catalog. The process of these two recommendation algorithms is similar: the user inputs his/her requirement, and the system gives the recommended resources based on that requirement and the reason for the recommendation. If the system fails to make an effective recommendation, the user is required to correct his/her requirement input.

The difference between the two lies in how the knowledge provided by the user is used to achieve personalized recommendations. The former relies on a pre-set set of recommendation rules, while the latter focuses on combining multiple similarity measures to determine similar resources.

However, the disadvantage of knowledge-based recommendation algorithms is that the quality of the recommendation application depends on the quality of the underlying knowledge base. In addition, the process is also overly dependent on user feedback, and when the user's needs change, the recommender system is unable to actively adapt to the user's new needs, and requires the user to actively modify their needs in order to obtain new personalized recommended content.

2.1.1 Item-based CF

In the following, we will mainly introduce the item-based collaborative filtering algorithm (Item-based CF) among the traditional nearest-neighbor collaborative filtering algorithms.Item-

based CF generally requires the following three computational steps: data representation, nearest-neighbor set generation, and recommendation results.

(1) Data Representation

The user-item rating matrix is generally denoted as $R_{n\times m}$, where nxm represents that there are n users and m items in the system, and rij denotes the rating value of user i for item j. If the user is implicitly interacting with the item, e.g., like/tap, unpurchased/purchase, click/slide over, etc., the rating value can be shown in binary (0 and 1). If the user is actively rating the item, the actual rating or normalized value is used as the rating value.

(2) Nearest Neighbor Set Generation

Nearest neighbor set generation is a key step in collaborative filtering algorithm. In Item-based CF, the common methods to calculate the similarity of items are: cosine similarity, improved cosine similarity, and Pearson correlation coefficient.

Before presenting the definitions of the coefficients, assume that r_{ai} and r_{aj} denote the ratings of the item i, j by user a, respectively. $U_{ij} = \{a \in U \mid r_{ai} \neq \phi$ and $r_{aj} \neq \phi\}$ denote the users who have rated the item i, j at the same time where U denotes the entire user space.

(a) Cosine similarity

Item-basedCF treats the rating data of each item as a vector on the n-dimensional user space. The similarity between two items is measured by calculating the cosine value between the vectors. If the item similarity is greater then the cosine value tends to 1. Assuming that the rating vectors of items i and j on the jointly rated user set U_{ij} are denoted as $\vec{i}$ and $\vec{j}$, the cosine similarity of items i and j is defined as follows:

$$sim(i, j) = \cos(\vec{\imath}, \vec{\jmath}) = \frac{\vec{i} \cdot \vec{j}}{\left\|\vec{i}\right\|_2 \times \left\|\vec{j}\right\|_2} = \frac{\sum_{a\in U_{ij}} r_{ai} \cdot r_{aj}}{\sqrt{\sum_{a\in U_{ij}} r_{ai}^2 \sum_{a\in U_{ij}} r_{aj}^2}} \tag{1}$$

(b) Improved cosine similarity

In order to eliminate the effect of different rating scales among users, the mean value of the corresponding user's rating is introduced to improve the appeal cosine similarity. The improved cosine similarity of items i and j is defined as follows:

$$sim(i, j) = \frac{\sum_{a\in U_{ij}} \left(r_{ai} - \overline{r_a}\right)\left(r_{aj} - \overline{r_a}\right)}{\sqrt{\sum_{a\in U_{ij}} \left(r_{ai} - \overline{r_a}\right)^2 \cdot \sum_{a\in U_{ij}} \left(r_{aj} - \overline{r_a}\right)^2}} \tag{2}$$

where $\overline{r_a}$ is the average of all ratings for user a.

(c) Pearson correlation coefficient

The Pearson correlation coefficient for items i and j is defined as follows:

$$sim(i, j) = \frac{\sum_{a\in U_{ij}} \left(r_{ai} - \overline{r_i}\right)\left(r_{aj} - \overline{r_j}\right)}{\sqrt{\sum_{a\in U_{ij}} \left(r_{ai} - \overline{r_i}\right)^2 \cdot \sum_{a\in U_{ij}} \left(r_{aj} - \overline{r_j}\right)^2}} \tag{3}$$

where $\overline{r_i}$ and $\overline{r_j}$ denote the mean value of ratings of items i and j on the set of users U_{ij}, i.e:

$$\bar{r}_i = \frac{\sum_{a \in U_{ij}} r_{ai}}{\left|U_{ij}\right|}, \bar{r}_j = \frac{\sum_{a \in U_{ij}} r_{aj}}{\left|U_{ij}\right|} \tag{4}$$

Using appeals or other methods of calculating item similarity, we can pre-calculate the similarity between all items, assuming that there exists a $m \times m$-order matrix $S(m,m)$ in the matrix. When it is necessary to use the nearest neighbor set of an item, the neighbors with greater than a preset threshold or top-k similarity are generally selected.

(3) Recommendation results

For the target user a, producing the recommendation result can be generally divided into two steps: firstly, predicting a's rating for the candidate item i, and finally selecting the set of items with rating top=N to recommend to the user.

Assume that item i has a set of nearest neighbor items $N(i) = \{s_1, s_2, \ldots, s_k\}$. When predicting the rating of item i by user a, it is easiest to think of using the ratings of the set of nearest neighbor items $N(i)$ to find the mean. However, it is important to note that the higher the similarity among the near-neighbor items, the higher the influence of the items should also be, so an improved weighted average method is as follows:

$$r_{ai} = \frac{\sum_{j \in I_{nei}} sim(i,j) \cdot r_{aj}}{\sum_{j \in I_{nei}} \left|sim(i,j)\right|} \tag{5}$$

where r_{aj} is the rating value of item j by user a, which can be obtained directly from the normalization of the rating matrix or approximated by a linear regression model r_{aj}'. Assuming that the rating vectors of item i and similar item j are $\vec{r}_i$ and $\vec{r}_j$, then $\vec{r}_j = \alpha \vec{r}_i + \beta + \varepsilon$, where the linear regression of the α and β model's training parameters, and ε is the model error.

Traditional collaborative filtering algorithms rely only on the user item interaction matrix, which is prone to data sparsity problems when they are applied to real commercial items, and the items for which the user has a record of operational behavior do not account for more than 1% of the total number of items. Using such a small amount of observed data to predict a large amount of unknown information will greatly increase the risk of overfitting. The cold-start problem can be counted as a special case of the data sparsity problem, which generally refers to the lack of necessary behavioral data for newly added users and items to make personalized recommendations.

2.1.2 Matrix decomposition

Most of the platforms that rely on recommender systems for intelligent recommendations support explicit feedback such as ratings. Assuming that the platform contains m users and n items, respectively, and the score of item i from user u is $r_{u,i}$, the $u-i$ rating matrix $R \in \mathbb{R}^{m \times n}$ can be constructed and has elements $R[u][i] = r_{u,i}$. The scale of users and items on general platforms is very large. The number of items visited and rated by users and the total number of their audiences are very small compared to this scale. Therefore, it is necessary to "fill" R through the mean method to obtain a dense matrix R_{dense}, and then represent it equivalents as the product of three low-rank matrices through SVD:

$$R_{dense} = U \Sigma V^T \tag{6}$$

where $U \in \mathbb{R}^{m\times k}, V \in \mathbb{R}^{m\times k}$, and $\Sigma \in \mathbb{R}^{k\times k}$ is the diagonal matrix with k singular values as diagonal elements. The new diagonal matrix $\Sigma_f \in \mathbb{R}^{f\times f}$ can then be customized to take the largest $f(f \leqslant k)$ singular value to construct the new diagonal matrix $\Sigma_f \in \mathbb{R}^{f\times f}$, and then the lower dimensionality user and item information matrices can be obtained by using f as a cut-off line, which is denoted respectively as $U_f \in \mathbb{R}^{m\times f}$ and $V_f \in \mathbb{R}^{n\times f}$, and substituting them into Eq. (6) can predict the missing rating values while restoring the observed R.

However, in the above method, it is necessary to open up a huge memory for R_{dense} and the computational cost of decomposing the commercial-quantity scoring matrix R is too high, following which a matrix approximation method is proposed:

$$R_{pred} = PQ^T \tag{7}$$

$$\hat{r}_{u,i} = \mathbf{p}_u \mathbf{q}_i^T = \sum_{k=1}^{K} p_{u,k} q_{i,k} \tag{8}$$

Eq. (8) is slightly different from Eq. (7), where $P \in \mathbb{R}^{m\times K}$ and $Q \in \mathbb{R}^{n\times K}$ record information about the platform users and items, respectively. Here the loss function can be written when using RMSE to measure the $r_{u,i}$ prediction effect:

$$\begin{aligned} \mathcal{L}(P,Q) &= \sum_{(u,i)\in \text{Train}} \left(r_{u,i} - \hat{r}_{u,i}\right)^2 + \text{reg}(P,Q) \\ &= \sum_{(u,i)\in \text{Train}} \left[\left(r_{u,i} - \mathbf{p}_u \mathbf{q}_i^T\right)^2 + \lambda\left(\left|\mathbf{p}_u\right|^2 + \left|\mathbf{q}_i\right|^2\right)\right] \end{aligned} \tag{9}$$

The above equation λ is the L2 regularization coefficient and can be continuously optimized to minimize $\mathcal{L}(P,Q)$ using batch-sample based gradient optimization algorithms such as SGD to minimize the P and Q parameters.

Three bias terms, platform-wide mean score μ, user-wide scoring habit B_u (with b_u to refer to u scoring habit), and item-wide word-of-mouth B_i (with b_i to refer to i scoring level), are added to the Bias SVD model. On this basis in view of ItemCF idea after that $\hat{r}_{u,i}$ is related to the user's u behavior on other items, and consequently add item i and j similarity $\omega_{i,j}$ to predict $\hat{r}_{u,i} = \frac{1}{\sqrt{|N(u)|}} \sum_{j\in N(u)} \omega_{i,j}$. But the item similarity matrix $W \in \mathbb{R}^{n\times n}$ is proportional to the square of the number of items n, and the information recording space is expensive, so the decomposition is also done for $\omega_{i,j}$:

$$\hat{r}_{u,i} = \frac{1}{\sqrt{|N(u)|}} \sum_{j\in N(u)} \mathbf{x}_i \mathbf{y}_j^T \tag{10}$$

The above equation replaces $\omega_{i,j}$ with two F-dimensional vectors $\mathbf{x}_i$ and $\mathbf{y}_j$, then the number of parameters required to describe the similarity of the n items in the platform decreases from n^2 to $2nF$ $(F \ll n)$. Combining the bias terms in the above equation, the

SVD + + model is proposed:

$$\hat{r}_{u,i} = \mu + b_u + b_i + \mathbf{q}_i \left(\mathbf{p}_u^T + \frac{1}{\sqrt{|N(u)|}} \sum_{j \in N(u)} \mathbf{y}_j^T \right) \tag{11}$$

Then under the RMSE loss function and L2 regularization constraints, the parameters can be iteratively updated by SGD as follows: η is the training learning rate, λ is the L2 regularization coefficient, and $e_{u,i}$ is the prediction error of the previous iteration. Eq:

$$e_{u,i} = r_{u,i} - \hat{r}_{u,i} \tag{12}$$

$$b_u \leftarrow b_u + \eta \left(e_{u,i} - \lambda b_u \right) \tag{13}$$

$$b_i \leftarrow b_i + \eta \left(e_{u,i} - \lambda b_i \right) \tag{14}$$

$$\mathbf{p}_u \leftarrow \mathbf{p}_u + \eta \left(e_{u,i} \cdot \mathbf{q}_i - \lambda \mathbf{p}_u \right) \tag{15}$$

$$\mathbf{q}_i \leftarrow \mathbf{q}_i + \eta \left[e_{u,i} \cdot \left(\mathbf{p}_u + \frac{1}{\sqrt{|N(u)|}} \sum_{j \in N(u)} \mathbf{y}_j \right) - \lambda \mathbf{q}_i \right] \tag{16}$$

$$\mathbf{y}_{j,k} \leftarrow \mathbf{y}_{j,k} + \eta \left(\sum_{j \in N(u)} \frac{e_{u,i}}{\sqrt{|N(u)|}} \cdot \mathbf{q}_{i,k} - \lambda \mathbf{y}_{j,k} \right) \tag{17}$$

Matrix decomposition makes full use of the user's rating history and the score information of the items in the candidate's neighborhood, and has better performance in rating prediction. Matrix decomposition needs to customize K hidden thematic factors to characterize users and items qualitatively, which is vague and results in poor recommendation interpretability. Moreover, the number of training parameters of this type of model is positively correlated with the number of users or the number of items, which makes it difficult to guarantee efficient recommendation service on platforms with a large number of users and millions of items, and has the defects of high memory requirement and high computation capacity.

Therefore, this paper proposes a personalized knowledge recommendation model based on constructivist learning theory, and combines the matrix decomposition idea to improve the design of personalized intelligent recommendation system.

2.2 Personalized knowledge recommendation model based on construct theory

2.2.1 Constructing a Basic Framework for Recommendation Modeling

There are two main issues to consider in constructing a recommendation model:

(a) How to represent the user's current knowledge experience.

(b) How to introduce new knowledge that is most suitable for constructive learning in the next moment based on the existing knowledge experience.

Based on the form of knowledge network graph coverage to help users gradually construct

learning to improve their own knowledge, and use the knowledge of the learning support degree to assess the user's new knowledge can be learned to construct the priority.

The framework of the constructive recommendation model is shown in Figure 1, which is mainly composed of two parts: the knowledge network module and the constructive recommendation module.

Knowledge network is a knowledge environment with interconnections between nodes, where nodes represent knowledge units and edges represent correlations between knowledge units. According to different entity units, nodes can be papers, patents, books, keywords, etc. According to different knowledge associations, edges can be citation relationships, co-occurrence relationships, cooperative relationships, etc.

The construction of knowledge network includes: knowledge term extraction, word vector modeling, and generating knowledge network by semantic distance constraints. In this way, the user knowledge context can be considered as a substructure of the knowledge network, representing the subsystem of knowledge that the user has learned. Another core of the modeling framework is the construct recommendation module, whose main task is to establish the logical association between the user's existing knowledge and the demanded knowledge through the knowledge network, and to analyze the user's knowledge demand and recommend the new knowledge with the most constructive learning value for the user.

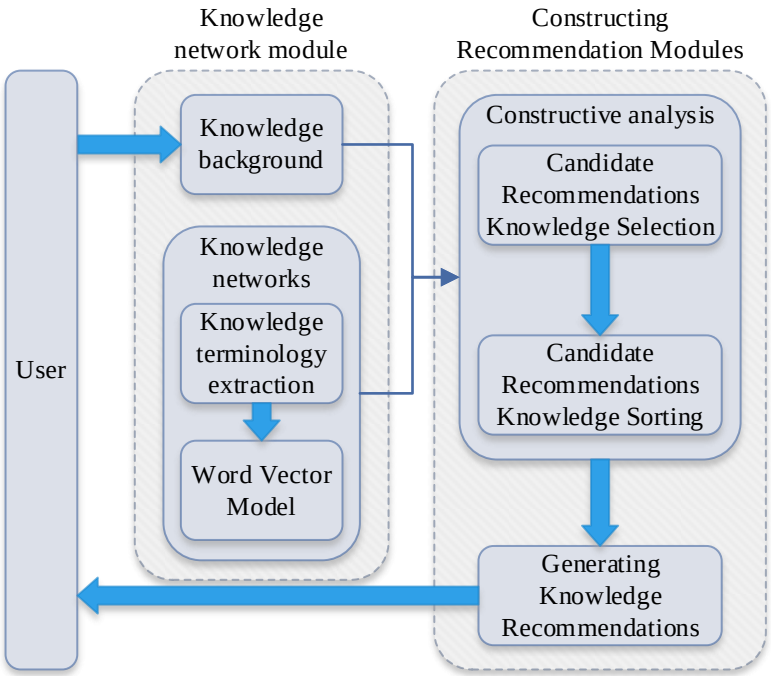

Figure 1: Construct the recommendation model framework

(1) Knowledge network module

Knowledge term extraction: In practice, information entropy and word frequency can be combined to generate a comprehensive weight for each candidate term, sorted by weight size, and select the top N candidate terms with significant weight as the final knowledge term.

Word vector model: the constructed recommendation model uses Word2Vec tool to train word vectors. Comprehensively, Negative Sampling based CBOW model is used in the model to train word vectors [24].

Knowledge network construction: based on the word vectors corresponding to each knowledge term obtained, the possible knowledge relationships between the knowledge can be calculated by mathematical operations between the word vectors, and the valid knowledge

relationships can be stored to finally build a complete knowledge network.

(2) Constructive recommendation module

The main task of constructing recommendation is to analyze the user's knowledge needs in combination with the knowledge network, so as to generate a semantically continuous recommendation sequence for the user. The constructive recommendation module mainly includes two parts: candidate recommendation knowledge extraction and candidate knowledge sorting output.

Candidate recommendation knowledge is considered to extract no more than N unlearned knowledge from the associated knowledge of recently learned knowledge sequences. Candidate knowledge sorting output recommends the introduction of support metrics as sorting quantities. For this purpose, the following definition of support knowledge is first introduced.

Definition 1: Let the knowledge b have a near-neighborhood relationship with a and let b be the top-M-nearest neighbor of a, denoted as $a \leftarrow b$, then b is said to be the supporting knowledge of a, and a is also said to be the epistemic knowledge of b.

The set consisting of all supporting knowledge of knowledge a can be set as the set of supporting knowledge of a, denoted as S_a. The support knowledge set of knowledge t is S_t.

The concept of support degree is introduced, which indicates the degree to which the user's current learned knowledge is directly constructible to new knowledge. The support degree of any knowledge t with respect to the user's current state is denoted as $W_s(t)$, which is defined as follows:

$$W_S(t) = \sum_{s_i \in \overline{S}_t} Sim(t, s_i) / \sum_{s_j \in S_t} Sim(t, s_j) \tag{18}$$

$$Sim(t, s) = \exp\left(-d_{ts}^2 / \left(2\sigma^2\right)\right) \tag{19}$$

where S_t denotes the set of supporting knowledge of knowledge t and $\overline{S}_t$ denotes the subset of learned knowledge in S_t. exp() denotes the exponential function, d_{ts} is the distance between knowledge t and s, and σ is the scale factor.

2.2.2 Model realization

(1) Constructivist Recommended Strategies

The core of constructivist learning theory lies in constructive cognition, in which learners acquire new knowledge through the construction of acquired knowledge.

(2) Description of constructive recommendation algorithm

Based on the above constructivist recommendation strategy, this subsection describes the process of constructive recommendation algorithm. Algorithm input for the user's initial background knowledge, and then continuously recommended to give the user the most learning value of the top-K learning knowledge items, the user selects one of the knowledge to learn, the formation of new background knowledge, so that iterative, the user's knowledge to get progressive growth.

3 Intelligent design for self-improvement of teachers' teaching skills

3.1 Overall Architecture of Personalized Intelligent Recommendation System

The personalized intelligent recommendation system can recommend the information that the user is interested in to the user by filtering the relevant information, such as movies, music, books, pictures and so on.

The overall architecture of personalized intelligent recommendation system is shown in Figure 2. This research takes network resource knowledge as an example to design and analyze the intelligent recommender system under data mining technology, with the ultimate goal of combining the user's (teacher's) preferences, the recommender system provides a filtered list of network resource knowledge recommendations for the user, and can be updated in a timely manner.

The system is designed in a three-tier architecture. When the user sends a command to the demanded information, the interface will pass the command to the middle layer. The search engine in the middle layer combines the user's preferences with the content in the multimedia library to generate media information that meets the user's criteria and feeds it back to the user interface. The user can pay and browse the recommended content if he is satisfied with it. The designed intelligent recommendation system consists of user processing subsystem, administrator control system and recommendation subsystem.

(1) User processing subsystem: This subsystem mainly collects users' personal information and provides users with functions such as registering and watching video related information. It includes list recommendation, hotspot analysis, categorized list, information search and so on.

(2) Administrator control system: Timely updating and maintenance of multimedia database, user or media information can be deleted. On the search engine, parameters can be adjusted. The administrator can manage the user database and automatically update the personalized information of the system.

(3) Recommendation subsystem: this subsystem mainly generates association rules to provide information recommendation at the fastest speed.

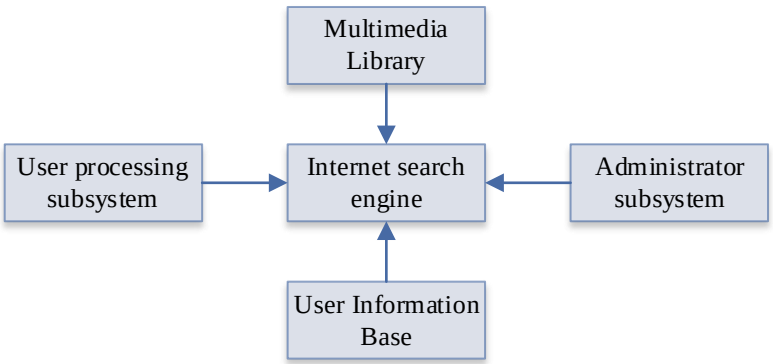

Figure 2: Personalized intelligent recommendation system framework

3.2 Personalized Intelligent Recommendation Module

Improve the matrix decomposition in the intelligent recommendation of the platform exists in the memory, computational volume defects, the design of the user characteristics generated by

the user, information matching and generation of recommendation of the three parts of the composition of big data recommendation module. Through the collection of massive user interest and use demand data, based on the recommendation algorithm to implement the calculation and selection, statistics and extract the score to obtain the optimal recommendation results. The overall structure of the intelligent recommendation module is shown in Figure 3.

The big data recommendation module includes three analysis processes:

(1) Generate user feature vector: the user's behavioral characteristics include the user's personal hobbies and usage data, etc. The system will convert the user's behavioral characteristics into data and generate feature vectors.

(2) Preliminary selection of recommendation results: Based on the category of data and preliminary selection, the system selects data similar to the user feature vector and generates a data table.

(3) Final Selection of Recommendation Results: The module performs statistics and arranges the data table selected in step 2, and obtains the final recommendation results.

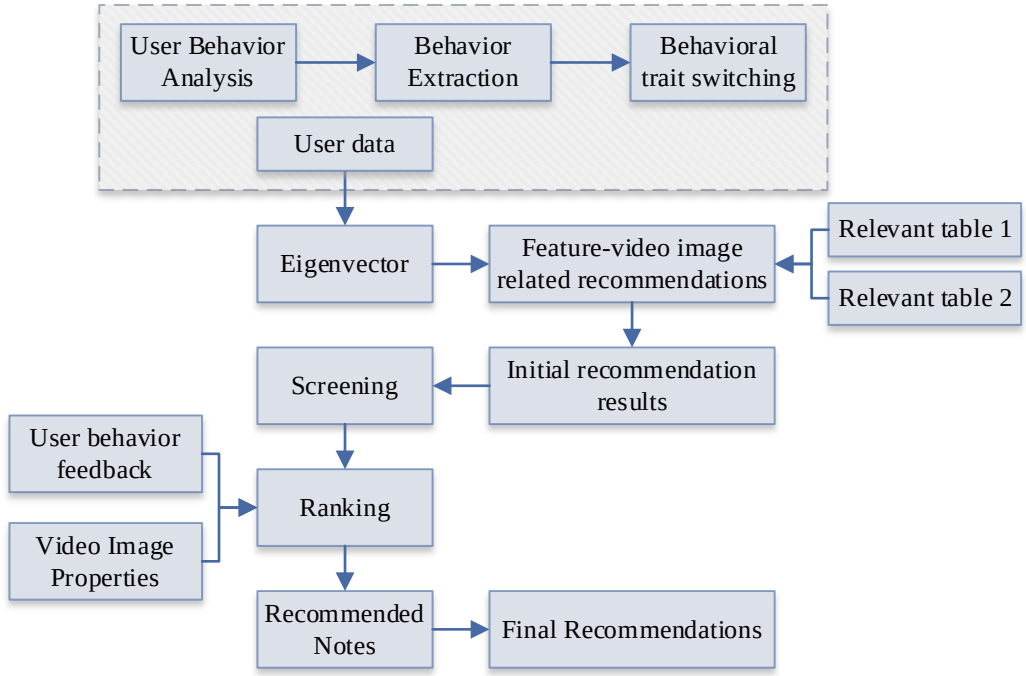

Figure 3: The overall structure of the intelligent recommendation module

3.3 Teaching Quality Assessment Module

There exists a better interactivity and usability of the teaching quality assessment module, which can provide functions such as teaching feedback, classroom discipline supervision and intelligent attendance. The structure of the teaching quality assessment module is shown in Figure 4. It consists of student terminals, classroom terminals, teaching terminals, teacher terminals and cloud servers to form the teaching quality assessment module. Each terminal and the cloud server are connected using mobile network communication.

The development of the client and classroom terminals is utilized to form the teaching quality assessment module through the combination with the cloud server and the construction of the background data. The module collects data from the classroom terminals through image processing technology, and in addition, the module is used for data transfer between the client, classroom terminals, and the database.

The classroom terminal is set in the classroom and includes a network communication sub-

module, a data collection sub-module, a terminal management sub-module and a frame processing sub-module.

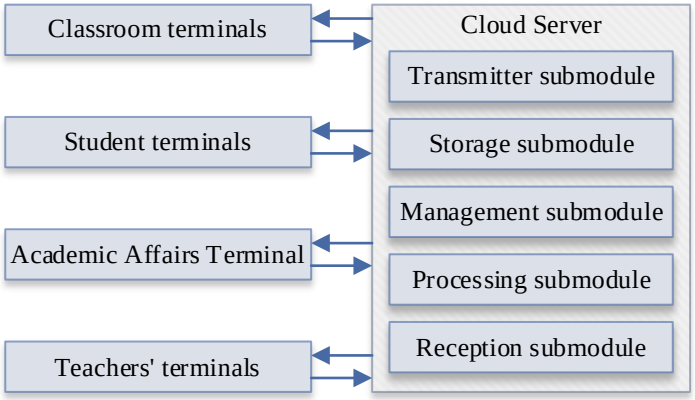

Figure 4: The structure of the teaching quality evaluation module

4 Self-improvement of teachers' teaching skills and realization of pedagogical development

4.1 Personalized Knowledge Recommendation

In this paper, two types of evaluation metrics commonly used in the recommendation domain are selected to assess the effectiveness of recommendation models.

(1) Hit rate (HR)

Hit rate is often used to measure the recall rate of the model in top-K recommendation, which is expressed as HR@K, and K is the number of recommendations. The formula is as follows:

$$HR@K = \frac{NumberOfHits@K}{RealResult} \tag{20}$$

This metric mainly reflects the effectiveness of the model recommendation results. The experiments in this paper mainly discuss the case of $K = 1,5,10$. Therefore, HR@1, HR@5, and HR@10 are adopted.

(2) Normalized Discounted Cumulative Gain (NDCG)

Firstly, we introduce the Discounted Cumulative Gain DCG, which is a score for the recommendation list that integrates the evaluation metrics that consider the relevance of the recommendation result position and the recommendation result in the recommendation list. It measures whether the recommendation result with higher relevance has a higher position in the list. Where K is the size of the recommendation list of top-K recommendations, and rel_i denotes the relevance of the i th recommendation result to the real recommendation result. The formula is as follows:

$$DCG_K = \sum_{i=1}^{K} \frac{2^{rel_i} - 1}{\log_2(i+1)} \tag{21}$$

NDCG is the result of the normalization process of DCG, and since the overall evaluation

of all teachers' recommendation lists needs to be completed, the DCG scores of different teachers' recommendation lists need to be normalized. The specific formula is as follows:

$$NDCG@K = \frac{DCG@K}{IDCG} \tag{22}$$

where IDCG is the ideal DCG maximum, i.e., the discounted cumulative gain calculated for the real recommendation list. The higher the NDCG indicator, the more likely it is that the knowledge points higher on the recommendation list are the ones teachers need.

4.1.1 Comparison of knowledge recommendation models

For the personalized knowledge recommendation method based on constructivist learning theory proposed in this paper, recommendation models that are also based on knowledge graph paths are selected for comparison:

(1) RKGE model

The path in this model consists of entities only, and uses the maximum pooling operation to extract the most significant features of multiple paths associated with a single knowledge point, and finally completes the recommendation through classification.

(2) KPRN model

The paths in this model consist of entities and relationships, and the importance of the paths is differentiated by dynamic weights, which are calculated in equation (22). The best performance is achieved with parameter γ=1. Finally the recommendation is accomplished by classification as well.

(3) KGPB model

Paths in this model consist of students, entities and relationships. The path weights are calculated by combining the knowledge scores. The final top-K recommendation is done using the BPR method.

(4) KGAB model

This model is oriented towards the personalized knowledge recommendation model KGPB proposed in the inquiry-based experimental course based on the study of adding student history information to assist recommendation. And the improvement of this recommendation model is made and KGAB model is proposed.

Several personalized recommendation models based on knowledge graph paths are shown in Figure 5.

It can be seen that the personalized knowledge recommendation method based on constructivist learning theory proposed in this paper performs best on the dataset.

This is reflected in the NDCG metric that indicates the importance of the order of the recommendation results: this paper's method (55.5%) improves by 8.8%, 13%, 16.2%, and 18.8% compared to the KGAB, KGPB, KPRN, and RKGE models.

The RKGE model improves HR metrics by 1% as the recommendation list expands, but does not differentiate between paths and does not focus on differences in user needs for knowledge points, and therefore performs the worst.

The KGPB model, in terms of path weight calculation, meticulously distinguishes the different needs of students for knowledge points by utilizing the information of specific scores of students' knowledge points, and thus outperforms the RKGE model and the KPRN model.

However, the personalized knowledge recommendation method based on constructivist learning theory proposed in this paper focuses on knowledge network construction, uses constructivist strategies, and thus performs best on the dataset.

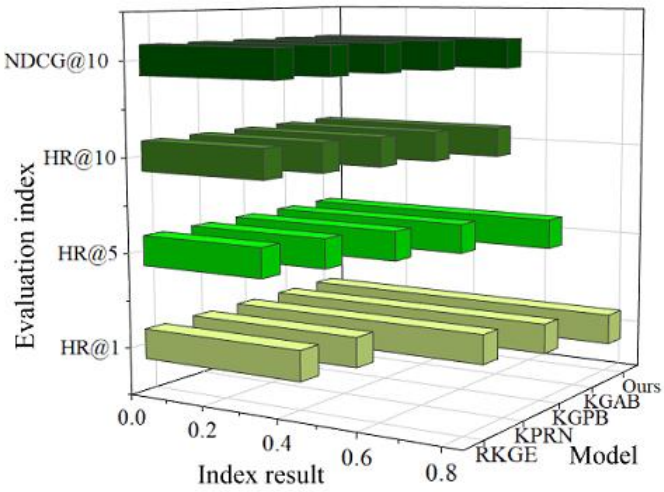

Figure 5: Several personalized recommendations model results

4.1.2 Recommendations for learning resources

(1) Experimental Data

In order to better target the group of teachers for learning resource recommendation, this section uses the self-collected MOOC Fundamentals of Computing online learning dataset to conduct experiments and conducts a comparative analysis with the implementation effects of other models to verify the effectiveness of the model in this paper.

The course data and teacher behavior data come from the online learning process of the Fundamentals of Computing course, a process that puts more emphasis on learners' self-study.

The dataset contains 300 learners, 1546 learning resources, and 3402 learning operation records. Each learner and learning resource has a unique corresponding id, which is denoted as 1 when there exists an interaction between user and item, and 0 otherwise, and each interaction record is also denoted by a unique num.

Meanwhile, in the experiment, this paper divides the data subset into training set and test set according to 8:2, and sets the ratio of positive and negative samples according to 1:1 in the training set.

Part of the data form is shown in Table 1.

Table 1: Partial data form

num	user_id	item_id	type
75	50	32	2
76	52	84	2
77	50	96	2
78	52	42	1
79	52	90	1
80	52	75	1
81	50	45	0
82	50	82	0

(2) Model Setup and Comparison Model

In the model of this paper, it is based on preference propagation for resource screening and recommendation, but in the online learning environment, a learner's ripple set will be larger, and in the process of preference propagation, when the hop value (hop) is too large, it will bring

too much noise data, which will weaken the effect of preference discovery instead, so with reference to the original RN model, the hop value is set to 3, the set value is set to 16, the learning rate is 0.03, and batchsize is 256.

In order to verify the effectiveness of the model in this paper, the following five models are mainly selected to compare and evaluate with the recommendation model in this paper.

(a) Collaborative filtering (CF) model

(b) RippleNet model

(c) PR-RippleNet model

(d) Knowledge Graph Convolutional Network (KGCN)

(e) PRPM-RN recommendation model, an improved method based on the RippleNet model.

(3) Model evaluation results

The evaluation results of the five models obtained through experiments are shown in Figure 6.

From the evaluation results, it can be seen that the performance of this paper's model is better in both ACC and AUC, which indicates that this paper's model can better recommend learning resources with the help of knowledge graph.

Among them, the traditional CF model has an evaluation value of ACC=0.563 and AUC=0.589, which are both around 0.5, indicating that its results have no reference value to a large extent and are largely random predictions.

Compared with other models, the model in this paper achieves an AUC of 0.902, with better overall performance and more comprehensive recommendation results.

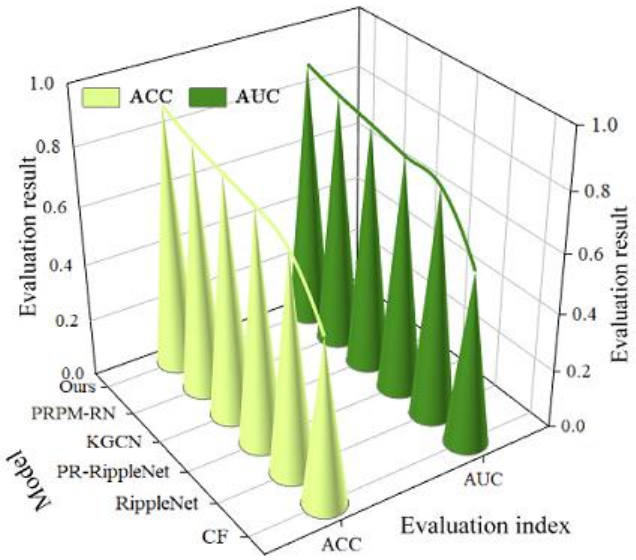

Figure 6: Evaluation results of 5 models

4.2 Teachers' capacity for self-improvement

In order to apply the intelligent design of teachers' self-improvement of teaching skills proposed in this paper, this paper implements a full semester of teaching practice in a secondary school. Taking professional teachers as the research object, the Teaching Quality Assessment Module was used to analyze the development of teachers' self-improvement ability from three aspects: overall situation, dimensional performance and individual differences. Individual differences are mainly analyzed based on teachers' basic information, so as to understand the development of self-improvement ability of teachers of different ages in different subjects, and to verify the feasibility of the personalized intelligent system designed in this paper.

4.2.1 Overall situation

This paper assesses teachers' self-improvement development in three dimensions: awareness enhancement, learning enhancement, and practice enhancement. Self-improvement awareness includes: awareness of needs, awareness of learning, awareness of practice, awareness of professional development, and lifelong awareness. Self-improvement learning includes independent learning related knowledge, independent learning related skills, and group learning related knowledge and skills. Self-improvement practice includes carrying out teaching preparation, carrying out teaching activities, and carrying out teaching management.

The overall assessment results of teachers' self-improvement are shown in Figure 7.

The intelligent module of teacher self-improvement designed by combining the personalized knowledge recommendation model of constructivist learning theory can achieve the growth of teachers' self-improvement awareness, learning, and practice. The following is the overall level of self-improvement development of teachers in this secondary school.

Self-improvement awareness in awareness of needs (82.16), awareness of learning (85.94), awareness of practice (74.57), awareness of professional development (81.94), and awareness of lifelong (72.68).

Self-improvement learning in independent learning related knowledge (78.98), independent learning related skills (74.51), group learning related knowledge (69.84) and skills (66.77).

Self-improvement practice, on the other hand, includes carrying out teaching preparation (89.57), carrying out teaching activities (70.54), and carrying out teaching management (82.98).

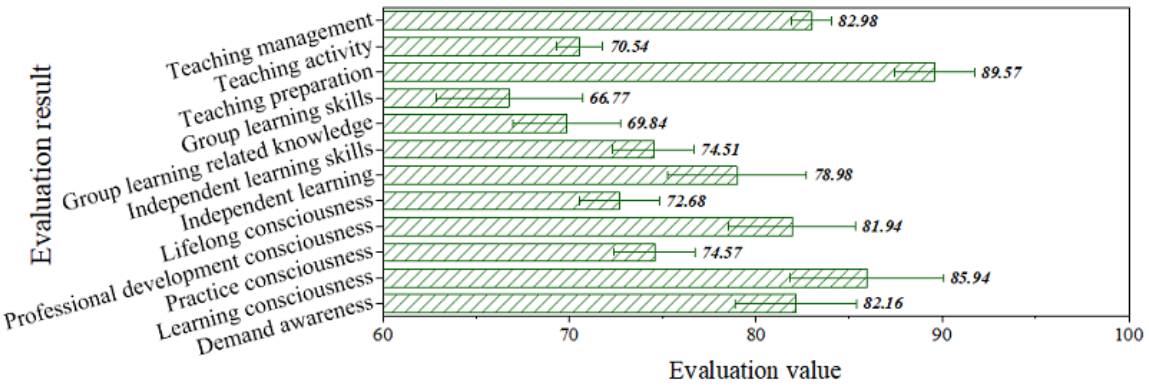

Figure 7: The overall assessment of teachers' self-improvement

4.2.2 Dimensional performance

The performance of teachers' self-improvement skills in terms of their teaching classes was assessed in terms of the three dimensions of awareness enhancement, learning enhancement, and practice enhancement. The study involved a total of 30 teachers in a total of 10 teaching classes.

The assessment results of the multi-class awareness dimension are shown in Figure 8. The mean value of the self-improvement awareness assessment for the ten teaching classes was 80.214. The level of self-improvement awareness was best developed in the case of Class 1 teachers, whose self-improvement awareness was rated at 86.25. And there are instances where teachers of class 4 and class 5 have low awareness of self-improvement. However, the overall self-improvement awareness of the teachers in the school is at a good level.

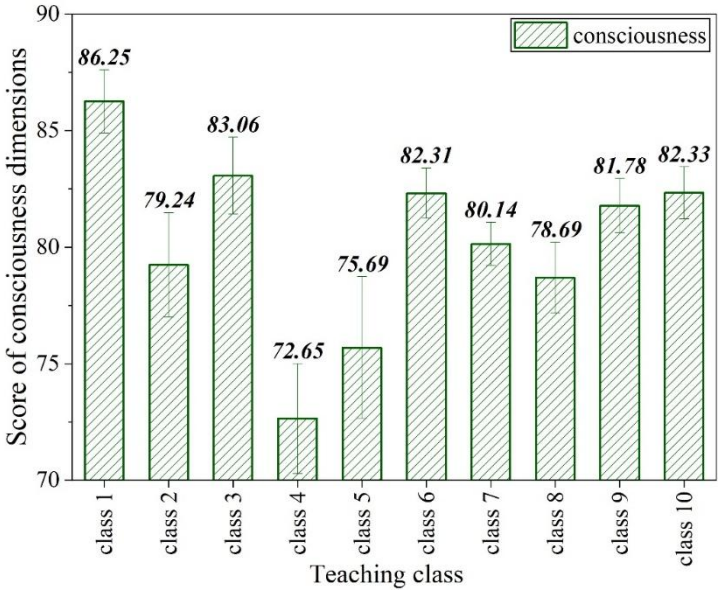

Figure 8: The evaluation results of multi-class consciousness dimensions

The results of the assessment of the learning dimensions for multiple classes are shown in Figure 9. This gives the self-improvement learning dimension scores for each classroom teacher. The self-improvement learning dimension ratings of class 4 teachers were 7 points higher than the awareness dimension. The reason for this may be that the school's requirement for professional teachers pushes Class 4 teachers to conduct self-improvement schools.

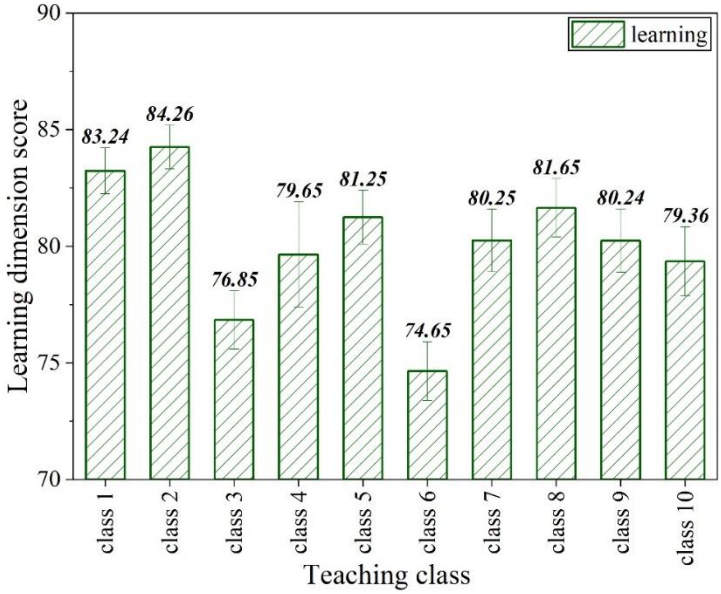

Figure 9: The evaluation results of multi-class learning dimensions

The assessment results of the multi-class practice dimension are shown in Figure 10.

Taking Class 4 as an example, the self-improvement practice level score of teachers in this class is 81.25, which is higher than that of other classes. The reason for this may be that teachers in this class fully and effectively used the personalized intelligent recommendation system to learn and absorb the recommended teaching resources. Overall, the mean value of the self-improvement practice scores of teachers in the 10 classes was 78.511.

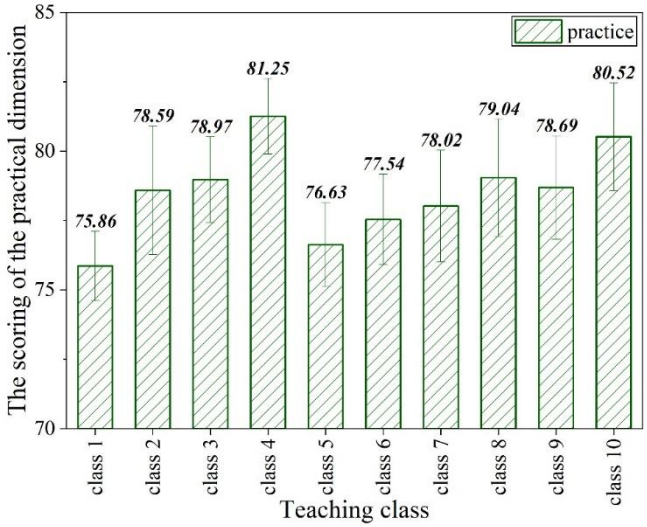

Figure 10: The evaluation results of multi-class practice dimensions

4.2.3 Individual differences

The age of teachers captured by the teaching quality assessment module designed in the previous paper was divided into four stages of 30 years old and below, 31-40 years old, 41-50 years old, and 50 years old and above for examination. The results of one-way ANOVA showed that there were significant differences in the dimension of self-improvement practices among teachers of different age groups, and there were no significant differences in the performance of other dimensions and the composite aspects.

The results of the test of variance of teachers' self-improvement ability in different age groups are shown in Figure 11.

Self-improvement awareness (78.65±2.54), self-improvement learning (73.54±2.68), and self-improvement practice (82.62±1.24) were higher among teachers aged 30 years and below than among teachers aged 50 years and above.

Self-improvement awareness (77.04±1.11) was higher than self-improvement learning (68.98±1.62), and self-improvement practice (75.19±1.36) among teachers above 50 years of age.

Among the four age division stages, professional teachers aged 31-40 years excelled in all aspects of self-improvement awareness, self-improvement learning, and self-improvement practice.

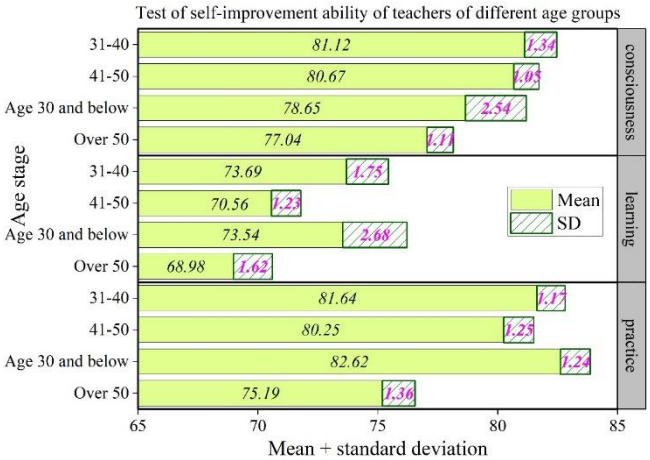

Figure 11: Test results of teachers' self-improvement ability in different age groups

5 Conclusion

This paper builds a personalized knowledge recommendation model based on constructivist learning theory and applies the model to the intelligent design of teachers' self-improvement of teaching skills. The level of teachers' self-improvement ability is analyzed in conjunction with the teaching quality assessment module.

The personalized knowledge recommendation model based on constructivist learning theory outperforms the KGAB, KGPB, KPRN, and RKGE models, and the HR@1, HR@5, and HR@10 values of this model are better than the comparative models when K takes the values of 1, 5, and 10, respectively. The recommended AUC and ACC of this model are 0.902 and 0.897 respectively for the online learning process of Computer Fundamentals course, and the recommended nature of learning resources fits the learning needs of professional teachers.

The overall assessment result of the Teaching Quality Assessment Module on the self-improvement ability of professional teachers is 77.54. By applying the intelligent design of self-improvement of teachers' teaching skills to teachers' teaching practice, the mean values of self-improvement of professional teachers' self-improvement awareness, learning, and practice scores of the ten teaching classes can be realized to reach 80.214, 80.14, and 78.511, respectively, and the application of personalized and intelligently-designed teaching is effective. .

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