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# Ubiquitous mobile systems in physical education: building adaptive learning environments and real-time interactive platforms

*Ping Xie*[1,2,*] *and Yong Chen*[2]

[1] Hunan Mass Media Vocational and Technical College, Changsha, Hunan, 410100, China
[2] Changsha Automotive Industry School, Changsha, Hunan, 410116, China

**SUMMARY:** *In this paper, an item-based collaborative filtering recommendation algorithm is first introduced to classify similar target users. After that, according to the characteristics of learners, the learning resource recommendation model is constructed based on the personalized recommendation of learners and learning resources to formulate a realistic learning plan. Finally, a real-time interactive intelligent data mining learning platform (DM_Edu) with self-adaptive learning environment is constructed, and the main architecture and module functions of the platform are constructed. The results show that the personalized learning resource recommendation algorithm proposed in this paper has better performance in accuracy, recall and F1-Score, and is an effective and feasible recommendation algorithm.The application results of the DM_Edu platform found that: teacher-student interactions in the theory classes of skill instruction classes present a large proportion of teachers' questions in classroom speech, and fewer interactions between teachers and students in speech, which are oriented by teachers' behaviors and the arrangement of classroom sessions. In the theory class of physical culture, teachers were good at receiving and expressing emotions, and conveyed the spirit and value of physical culture through emotional rendering; however, there was less teacher-student interaction, and the interactive atmosphere was not harmonious enough. In the theory class of health education, teachers are good at leading students to actively participate in the class through words, and teacher-student interactions are frequent; however, the class will be delayed resulting in incomplete class.*

***KEYWORDS:*** *Collaborative Filtering Recommendation Algorithm; Learning Resource Recommendation Model; Online Learning Platform; Physical Education*

## 1 Introduction

The rapid development of digital technology is profoundly changing the traditional pattern of physical education teaching, providing unprecedented possibilities for the innovation of teaching mode. The introduction of artificial intelligence, big data analysis and virtual reality not only breaks the time and space limitations of traditional teaching, but also provides students with a more personalized and precise learning experience [1]. With the help of smart wearable devices and motion sensors, students are able to obtain their own motion data in real time, so as to optimize the details of the movements under the guidance of teachers, and improve the science and effectiveness of training [2, 3]. At the same time, teachers can also use digital tools to monitor the students' learning process dynamically, adjust the teaching strategy in time, and realize the tailor-made teaching [4]. However, the wide application of technology also brings a

*18608413115@163.com
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series of practical problems such as data privacy protection is not in place, the high cost of technical equipment, and low digital literacy of teachers and students, etc. The solution of these problems requires universities to promote the process of teaching reform and ensure that the technology empowers, while taking into account the fairness and sustainability of education [5, 6].

Adaptive learning is an educational model that dynamically adjusts learning contents and paths based on learners' individual differences and needs to improve learning effects and satisfaction. Regarding the research on adaptive learning, Minn has sorted out the developmental lineage of student models in adaptive learning environments and constructed a cross-disciplinary analytical framework for knowledge assessment, which provides two-way theoretical references for educational researchers and AI experts; however, the study has not carried out empirical validation of specific technological paths, and the exploration of dynamic assessment needs in the emerging learning ecosystem still needs to be deepened [7]. Normadhi et al. addressed the problem of personal trait modeling of learners in adaptive learning environments, and for the first time systematically sorted out the common law of trait modeling of learners in this field, and clarified the dominance of learning styles and the technological tendency of automatic computer detection; however, this study failed to cover the new technological advances in recent years, such as deep learning, and did not provide empirical comparisons of the actual teaching effects of various types of trait recognition techniques [8]. Peng et al. systematically constructed a theoretical framework and methodological system for personalized adaptive learning in smart learning environments, adopting a combination of theoretical construction and model design, proposing a four-dimensional framework, and further developing a learner portrait and path recommendation model; however, the study has not yet explored the path of specific technological implementation and multi-scenario applicability in depth [9]. El-Sabagh constructed an adaptive learning system based on learning style theory and empirically tested it through a quasi-experimental design with a learning engagement scale (covering four dimensions: skill, participation, performance, and emotion), and found that adaptive learning environments have a significant role in enhancing students' engagement; however, the study did not delve deeper into the effects of different disciplinary backgrounds, cultural environments, or technological conditions on the effectiveness of adaptive learning [10]. Chrysafiadi et al. introduced an intelligent guided learning system for teaching C programming, which realizes adaptive adaptation of learning content and teaching sequence by combining machine learning and fuzzy logic techniques [11].

The data-driven adaptive learning model is one of the core directions of the digital-enabled physical education teaching reform, which centers on the accurate capture and deep mining of students' athletic performance through intelligent devices and data analysis technology [12, 13]. Kilaru et al. explored an adaptive physical education platform based on machine learning and Internet of Things (IoT) technology, combining IoT wearable devices to collect students' physiological data in real time, and utilizing a decision tree model for the association analysis of curriculum content and physical activity to enhance the personalization of physical education and health monitoring effects; however, the study has not yet explored in depth [14]. Susanto and Afandi developed physical education learning products adapted to the requirements of an independent curriculum through a common application to support teachers in adapting teaching and learning tools to the needs and interests of their students and to build a framework of programs to strengthen students' Pancasila literacy based on themes set by the government [15]. Saputra et al. developed and validated a creative adaptive physical education learning model for special needs students aimed at enhancing their participation in physical activities, and empirical evidence showed a significant increase in student participation to 86.94% ($p<0.05$) after the implementation of the model, and parental feedback confirmed a positive impact in

multiple dimensions such as social and emotional [16]. Colquitt et al. systematically elaborated a framework for the application of the personalized teaching model in physical education by integrating multidimensional assessment of students' readiness, interest and learning characteristics, providing physical education teachers with hands-on strategies for diverse learners, sorting out the logic of its implementation in the traditional classroom, and focusing on physical education teaching scenarios to propose adaptive adjustments [17].

In addition, Koh used multilevel modeling with a quadratic growth curve model to investigate the effects of integrating an adaptive physical education curriculum and individualized education program training on Korean preservice physical education teachers' self-efficacy for inclusive education, aiming to reveal the sustained promotion of self-efficacy by combining the courses and to provide empirical evidence for the integration of curricula in preservice teacher education [18]. Miao et al. for the first time in the field of physical education integrated multidisciplinary theories to construct a systematic framework for personalized learning trajectories, and realized the coherence from the theoretical to the operational level through technological empowerment, which provided a landable solution for smart physical education [19]. Kokaridas et al. aimed to develop a new Individualized Education Program (IEP) assessment tool for physical education teachers through a dynamic assessment procedure in order to test its value in improving their educational knowledge, focusing on differences in their attitudes when using the dynamic assessment tool and its relationship with teaching experience and school resource conditions [20]. Patrascu et al. focus on the personalized application of AI technology in the field of physical education and athletic training, adopting a combination of cross-disciplinary literature review and case study to sort out the practical path of AI technology in physical education, and also deeply analyze the constraints of socio-cultural factors on the landing of the technology [21]. Information technology-enabled sports adaptive learning refers to relying on a new generation of information technology such as big data, artificial intelligence, and the Internet of Things to build a sports learning support system of dynamic perception, accurate diagnosis, intelligent recommendation and real-time feedback centered on learners' individual physical conditions, athletic abilities, interest preferences, and developmental needs, and to achieve personalized customization and adaptive optimization of the sports teaching and training process [22, 23]. The core of the system is to transform the traditional standardized and scaled sports teaching into a precise education model that takes learners' individual differences as the starting point, and empowers learners to realize the effective improvement of physical literacy and sports skills on the appropriate development path [24].

The article firstly introduces the features and structure of the project-based collaborative filtering recommendation algorithm and matrix decomposition recommendation algorithm in detail, which provides technical support for constructing an adaptive learning environment and real-time interactive physical education teaching platform. Then, according to the characteristics of the adaptive learning system and its objectives, the learners and learning resources are modeled separately, and the learning resource recommendation model is proposed. After that, based on the collaborative filtering recommendation algorithm and learning resource recommendation model, an intelligent data mining learning platform (DM_Edu) is designed. The platform contains three system architectures: resource layer, management layer and intelligent layer, and five functional modules: teaching, learning, management, big data analysis and intelligent assisted learning. Finally, taking the physical education courses in DM_Edu platform as an example, the interaction process between teachers and students in three types of physical education courses is analyzed, and the process is coded, classified and parsed.

# 2 Learning platform based on adaptive learning environment and real-time interaction

## 2.1 Collaborative Filtering Recommendation Algorithm

Recommendation algorithm is the most core technology in a recommendation system, according to the different recommendation processing strategies, the currently used recommendation algorithms can be broadly categorized into the following four categories: content-based recommendation algorithm (CB), collaborative filtering recommendation algorithm (CF), recommendation algorithm based on deep learning (DB) and hybrid recommendation algorithms (HR).

In a large platform there are generally very many programs and the possibility of different users choosing the same program is very low, resulting in the target user not being able to find users similar to them. Moreover, in a large platform, the growth rate of users is much larger than the growth rate of projects, and the projects are relatively stable, so in this paper, project-based collaborative filtering is selected as one of the recommendation algorithms. The matrix decomposition of the recommendation algorithm has a strong generalization ability, which solves the problem of matrix sparsity to a certain extent, and it has a low space complexity, which only needs to store the hidden vectors of the items and the users, so it is selected as another recommendation algorithm based on the matrix decomposition in the model. The item-based collaborative filtering recommendation algorithm and the matrix decomposition in model-based recommendation algorithm used in this paper are described in detail below.

### 2.1.1 Item-based collaborative filtering recommendation algorithm

Item-based collaborative filtering recommendation algorithm is based on the user's historical preference for items to calculate the similarity between different items, and then based on the similarity to predict the unrated item rating and calculate the target user recommendation results.

The process of item-based collaborative filtering recommendation algorithm is as follows:

(1) Calculate the similarity between items

According to the definition of item-based collaborative filtering algorithm, the following formula for calculating the similarity of items can be derived:

$$S_{ij} = \frac{\left|N_i \cap N_j\right|}{\left|N_i\right|} \tag{1}$$

In this formula, the denominator $\left|N_i\right|$ denotes the number of users who like item $i$, and the numerator denotes the number of users who like both item $i$ and item $j$. However, this formula is not reasonable, if project $j$ is a very popular project, almost everyone likes $j$, then the similarity between the two projects $i, j$ will be very close to 1. So the following formula is proposed:

$$S_{ij} = \frac{\left|N_i \cap N_j\right|}{\sqrt{\left|N_i\right|\left|N_j\right|}} \tag{2}$$

The improvement of this formula is that if item $j$ is a very popular item, the denominator becomes correspondingly larger, i.e., the weight of the popular item $j$ is reduced, decreasing

the likelihood that the popular item is particularly similar to the other goods. To solve this problem, Pearson's correlation coefficient is proposed to find the similarity between two items:

$$S_{ij} = \frac{\sum_{p\in P}\left(R_{pi} - \bar{R}_i\right)\left(R_{pj} - \bar{R}_j\right)}{\sqrt{\sum_{p\in P}\left(R_{pi} - \bar{R}_i\right)^2}\sqrt{\sum_{p\in P}\left(R_{pj} - \bar{R}_j\right)^2}} \tag{3}$$

where $P$ denotes the set of users, $\bar{R}_i$ denotes the average of all users' ratings for item $i$, and $\bar{R}_j$ denotes the average of all users' ratings for item $j$.

(2) Personalized recommendation based on the similarity between items and the user's historical behaviors

After obtaining the similarity between items, item-based collaborative filtering calculates the degree of interest of a user $u$ in an item $j$ by the following formula:

$$\hat{R}_{uj} = \frac{\sum_{i\in N(u)\cap L(j,K)} S_{ij} R_{ui}}{\sum_{i\in N(u)\cap L(j,K)} S_{ij}} \tag{4}$$

where $N(u)$ denotes the set of items that user $u$ likes, $L(j,K)$ denotes the $K$ items that are most similar to the item, $S_{ij}$ is the similarity between item $i$ and item $j$, and $R_{ui}$ is the degree of interest of user $u$ in item $i$. After obtaining the user's rating for each one, the $N$ items with the highest ratings are selected to recommend to the user.

### 2.1.2 Matrix Decomposition Recommendation Algorithm

The algorithmic procedure for matrix decomposition is as follows:

The objective of matrix factorization is to minimize the sum of squared errors and to complete the matrix factorization with minimum perturbation. Where $\vec{p}_u, \vec{q}_i$ are the $d$-dimensional vectors of the corresponding subscripts in the matrix $U_{m\times d}$ and the matrix $V_{n\times d}$, respectively. i.e:

$$\min_{\vec{p}_u,\vec{q}_i} \sum_{(u,i)\in K} \left(R_{ui} - \vec{p}_u \vec{q}_i^{\,T}\right)^2 \tag{5}$$

Matrix factorization is the decomposition of the original high-rank matrix $R_{m\times n}$ into two low-rank matrices $U_{m\times d}$ and $V_{n\times d}$ such that:

$$R_{m\times n} = U_{m\times d} V_{n\times d}^T \tag{6}$$

The values in matrix $U_{m\times d}$ and matrix $V_{n\times d}$ are randomly generated and will be iteratively optimized in the subsequent process until the matrix decomposition termination condition is satisfied.

Matrix decomposition is to predict the unknown data by the existing data in the original matrix, so in the process of decomposing the matrix, it is necessary to avoid overfitting the existing data in the original matrix by adding regular terms. So the following objective optimization function is proposed:

$$\min_{\vec{p}_u,\vec{q}_i} \sum_{(u,i)\in K} \left(R_{ui} - \vec{p}_u \vec{q}_i^T\right)^2 + \lambda\left(\left\|\vec{p}_u\right\|^2 + \left\|\vec{q}_i\right\|^2\right) \tag{7}$$

The constant $\lambda$ controls the degree of regularization and avoids overfitting the scored data.

When using stochastic gradient descent to reduce the sum of squares of errors, the error is first defined:

$$e_{ui} = R_{ui} - \vec{p}_u \vec{q}_i^T \tag{8}$$

Use the objective optimization function to find the partial derivatives of $\vec{p}_u, \vec{q}_i$:

$$\frac{\partial f(\vec{p}_u, \vec{q}_i)}{\partial \vec{p}_u} = -2e_{ui}\vec{q}_i + 2\lambda \vec{p}_u \tag{9}$$

$$\frac{\partial f(\vec{p}_u, \vec{q}_i)}{\partial \vec{q}_i} = -2e_{ui}\vec{p}_u + 2\lambda \vec{q}_i \tag{10}$$

The $\vec{p}_u, \vec{q}_i$ is then updated in the opposite direction of the bias:

$$\vec{p}_u = \vec{p}_u + \eta\left(e_{ui}\vec{q}_i - \lambda \vec{p}_u\right) \tag{11}$$

$$\vec{q}_i = \vec{q}_i + \eta\left(e_{ui}\vec{p}_u - \lambda \vec{q}_i\right) \tag{12}$$

$\eta$ is the step hyperparameter.

It usually takes several iterations to complete the decomposition of a high-rank matrix, and there are three common iterative termination conditions for matrix decomposition as follows:

(1) Setting a threshold $\gamma$ and stopping the iteration when the sum of error squares is less than the threshold.

(2) Set a threshold $\gamma$, and stop iterating when the absolute value of the first and last two function value changes is less than the threshold.

(3) Set a fixed number of iterations.

After obtaining the matrices $U$ and $V$, the following formula is utilized to predict the unrated data of user $u$ on item $i$:

$$\hat{R}_{ui} = \vec{p}_u \vec{q}_i^T \tag{13}$$

In this way, the user's ratings for unrated items can be predicted and personalized recommendations to the user can be accomplished.

## 2.2 Adaptive Learning Resource Recommendation Model for Sports

### 2.2.1 Learner model

(1) Learner modeling standards

Learner metadata standards are formulated to realize the migration and sharing of learner information on different platforms under the premise of data security and integrity.IEE and PAPIIMSLIPS and CELTSll make a one-by-one introduction on the three standards.

1) IEEEPAPI

PAPI is a learner information standard developed by LTSC under IEEE. The standard includes six categories of information: Learner Personal, Learner Performance, Learner Relation, Learner Security, Learner Portfolio, and Learner Preference.

2) IMS LIPS

IMS LIPS is designed to ensure the exchange of learner information between different information systems, such as learning management systems, knowledge management systems, student information systems, and corporate e-learning systems. The standard includes Identification, Accessibility, Goal, Activity, Competency, Interest, Afiliation, Transcript, Security Key, Relationship.

3) CELTS-11

Learner information is created by the learning system, instructor, student, or other entity. Learner information consists of Personal Information, Academic Information, Management Information, Relationship Information, Security Information, Preference Information, Performance Information, and Portfolio Information.

(2) Key points of learner modeling

The key to constructing a learner model is how to determine a framework that meets the requirements based on the purpose of the learning system and on the basis of the aforementioned learner criteria.

1) Adaptive source

The adaptive source is the personalized characteristics of the learner on which the learner model is based. Based on the relationship with the domain, personalized characteristics can be classified as domain-related or domain-independent.

2) Purpose of constructing the learner model

The aforementioned reference specification of learner model describes learner characteristics relatively comprehensively from the perspective of generality. However, different learning systems or platforms put forward different requirements for the construction of learner models.

(3) Construction of Learner Model

The learner model includes three elements of the learner, which are described as follows:

1) Knowledge level: refers to the degree of mastery of the relevant knowledge that the individual learner currently has. The level of mastery of a certain knowledge point is represented by $t_i$, which defines $K=\{(k_1,t_1),\cdots,(k_i,t_i),\cdots(k_n,t_n)\}$, where $k_i$ denotes the $i$ th knowledge point, $t_i$ denotes the level of mastery of the $i$ th knowledge point, $t_i \in T$, $T=\{0,1,2,3,4,5,6\}$, where 0 indicates that the knowledge point is a blind spot for the learner. To test the level of a certain knowledge of the learner, 1 means the answer is correct, -1 means the answer is wrong, 0 means that the test topic does not contain the knowledge point. Then the rate of correctness $r(h_i)$ for each level of knowledge $h_i$ is described as:

$$r(h_i)=\frac{Nh_i(1)}{Nh_i(1)+Nh_i(-1)}, i=1,2,3,\cdots,6 \tag{14}$$

where $Nh_i(1)$ denotes the number of times the learner answered correctly to a question with a test level of $h_i$; and $Nh_i(-1)$ denotes the number of times it was incorrect. Thus the feature vector $K$ of the learner's mastery of a certain knowledge can be obtained:

$$K=<r(h_1),r(h_2),r(h_3),\cdots,r(h_6)> \tag{15}$$

2) Cognitive ability: refers to the ability of individual learners to learn new knowledge. The learner's cognitive ability level for a certain knowledge point is expressed by $l_i$, defining $C=\{(c_1,l_1),\cdots,(c_i,l_i);\cdots(c_8,l_8)\}$, where $c_i$ indicates the $i$th cognitive ability, and $l_i$ is the level value of the $i$th cognitive ability. In order to obtain the cognitive ability of the learner, the type of test questions is designed:

$$TEST=\left(A,D,\beta,t_1,t_2\right) \tag{16}$$

where $A$ is the category of cognitive ability measured; $D$ is the standardized answer. $\beta$ is the difficulty coefficient; $t_1$ is the learner's response time; and $t_2$ is the learner's study time. The learner provides an answer $D_i$ to each test question $T_i$, and completing the test acquires the set of learners (test questions, answers):

$$Answer=\left\{\left(T_1,D_1\right),\cdots,\left(T_i,D_i\right),\cdots,\left(T_n,D_n\right)\right\} \tag{17}$$

Get the learner corresponding to a particular cognitive ability as:

$$l(A)=\frac{1}{n}\sum_{i=1}^{n}\frac{(D_i\cap D)\beta}{t_1t_2} \tag{18}$$

Thus the feature vector of the learner's cognitive ability is obtained:

$$R=<l(A_1),l(A_2),l(A_3),\cdots,l(A_8)> \tag{19}$$

3) Preference demand: refers to individual learners' personalized preference and demand for learning resources. According to the characteristics of this system, it is divided into strategy $(S)$: including demonstrative, inquiry, collaborative, etc., type $(T)$: video, PPT, text, etc. and implicit features $(R)$. Implicit features come from the interaction between learners and learning resources, which can indicate learning effects, feedback information, etc., and are feature vectors updated by VL2v model. Get the feature vector of learners' preference needs:

$$PR=<S,T,R> \tag{20}$$

The learner model is:

$$Learner = K\ concatenate\ R\ concatenate\ PR \tag{21}$$

To wit:

$$Learner=<r(h_1),r(h_2),\cdots r(h_6),l(A_1),l(A_2),\cdots l(A_8),S,T,R> \tag{22}$$

### 2.2.2 Learning resource model

Learning resources in this paper refer to the tools used to improve learners' knowledge. In this paper, we analyze the inherent characteristics and evaluation characteristics of learning resources in terms of their difficulty, quality and recognition in interaction with learners.

1) Inherent characteristics $O$: the characteristics of the learning resource itself, including

content $C$ and type $T$.

$$O =< C, T > \tag{23}$$

2) Evaluation features $(S)$: difficulty $(D)$, quality $(Q)$, recognition $(P)$, implicit features $(R)$. Implicit features come from the interaction between learners and learning resources, which can indicate learning effects, feedback information, etc., and are feature vectors updated through the VL2v model.

$$S =< D, Q, P, R > \tag{24}$$

Learning resources modeled as:

$$Resource = O \ concatenate \ S \tag{25}$$

To wit:

$$Resource =< C, T, D, Q, P, R > \tag{26}$$

### 2.2.3 Learning Resource Recommendation Model

The core and key of the learning resource recommendation function lies in researching a recommendation algorithm that meets the practical needs on the basis of adaptive learning system. Constructing a closed-loop adaptive learning resource recommendation model based on neural network is one of the solutions. The recommendation system adjusts the corresponding learning resource recommendation strategy to adapt to the current learner by analyzing the learner's feedback on various aspects of the learning resources.VL2v is able to learn both positive and negative relationships, and customize the characteristics of the learning object according to the actual needs.VL2v updates the implicit characteristics of the learner and the learning resources according to the learner's feedback on the learning resources, respectively, so that it can better capture the features for the next recommendation.

## 2.3 Adaptive Sports Learning Resources Recommendation Results and Analysis

### 2.3.1 Experimental data sources and parameterization

(1) Experimental data sources

The experimental data used in this paper comes from MOOCCube, an open dataset published by ACL2020.The dataset integrates data on courses, concepts, and students' behaviors, which is widely used in the field of education informatization research, and aims to support researchers working in the fields of natural language processing, data mining, and learning resource recommendation engaged in research related to large-scale online education. The dataset contains 706 real online courses, totaling 38,181 teaching videos, 114,563 concepts, and 8 million online learning records from 199199 MOOC users. Due to the huge amount of data in the original dataset, this paper randomly selected 1000 users' learning records from it as experimental data, containing 25342 historical behavioral data and 320 online courses. The number of courses selected by users is in the range of 1~10. In this section of the experiment, the experimental data are randomly divided, in which 70% of all data are used as the training set and 30% as the test set. Mean absolute error, accuracy, recall and F1-Score are used as

evaluation metrics.

(2) Related parameter settings

The initial value of the item penalty factor parameter is set to 1, the step size is 1, and the maximum value is 10. The initial value of the weight factor parameter is set to 0.05, the step size is 0.1, and the maximum value is 0.9. When the penalty threshold is 7, and the weight factor is 0.8, the evaluation indexes of this paper's algorithm reach the maximum value and the recommendation effect is the best. Therefore, the values of the penalty factor parameter and weight factor in the subsequent experiments are selected as 7 and 0.8, respectively.

### 2.3.2 Comparative analysis of similarity

In order to verify the effectiveness of Pearson similarity after the introduction of popular term penalty factor and common rating term penalty factor to improve Pearson similarity in this paper, the experiment compares the cosine similarity, Euclidean distance and Pearson correlation coefficient as the similarity calculation methods in this paper's algorithm with the improved Pearson similarity in this paper, respectively. For the MAE values of different similarity calculation methods under different number of nearest neighbor users k, the comparison results of MAE values of different similarity degrees are shown in Fig. 1. It can be seen that the MAE values of the four similarities first gradually decrease and then stabilize with the increase of the number of neighboring users k, and the improved similarity in this paper always has a smaller MAE value. Meanwhile, comparing the traditional Pearson similarity and the improved Pearson similarity of this paper, it can be seen that there is not much difference between the two in the MAE value when the k value is relatively small, however, as the k value increases, the Enhanced-Pearson of this paper decreases at a higher rate than that of the traditional Pearson similarity, which indicates that the introduction of the common scoring term penalizing factor and the popular term This indicates that the introduction of the common rating item penalty factor and the popular item penalty factor makes the prediction rating error of Enhanced-Pearson smaller, which proves that the improved Pearson similarity of this paper has better performance.

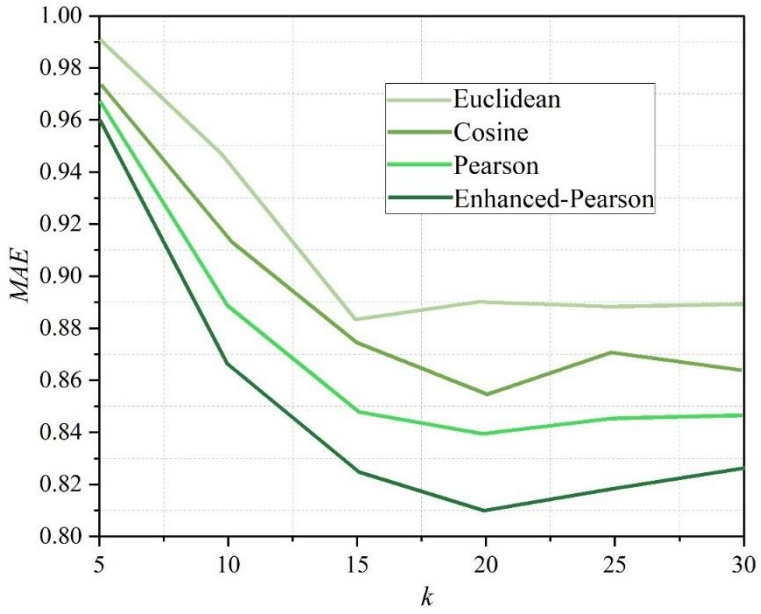


*Figure 1: Comparison of MAE values with different similarity levels*

### 2.3.3 Comparative analysis of algorithm performance

The comparison results of the accuracy, recall and F1-Score of the four algorithms under different values of k are shown in Figs. 2, 3 and 4. It can be seen that with the gradual increase of the number of neighboring users k, the evaluation indexes of this paper's algorithm and the four algorithms of “IAICUI, BBR and TCF” first increase rapidly to a certain value and then tend to stabilize. and the algorithm in this paper has the highest accuracy, recall and F1-Score when the value of the number of neighboring users k is around 16. Comparing the experimental results of this paper's algorithm and the IAICUI algorithm, it can be seen that when k is less than 10, the evaluation indexes of the two algorithms basically coincide. When the performance of this algorithm reaches the peak, the trend of the two algorithms is gradually consistent; comparing the experimental results of this paper's algorithm and the TCF algorithm, it can be seen that the overall performance of this paper's algorithm is much better than the TCF algorithm, and with the increase of k, the evaluation indexes of this paper's algorithm have obvious improvement, while the TCF algorithm's improvement is very weak.

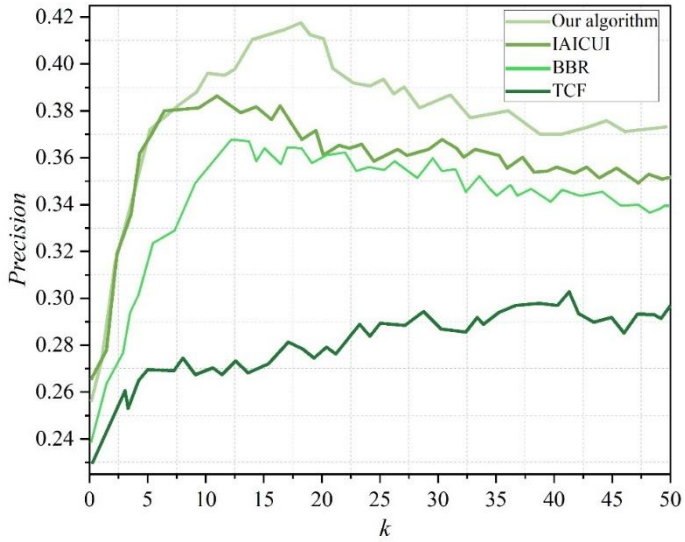


*Figure 2: Comparison of accuracy rates of four algorithms under different k values*

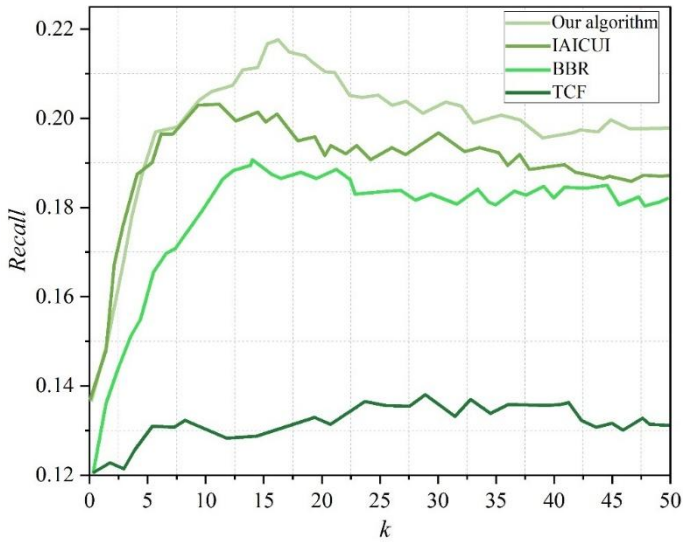


*Figure 3: Comparison of recall rates of four algorithms under different k values*

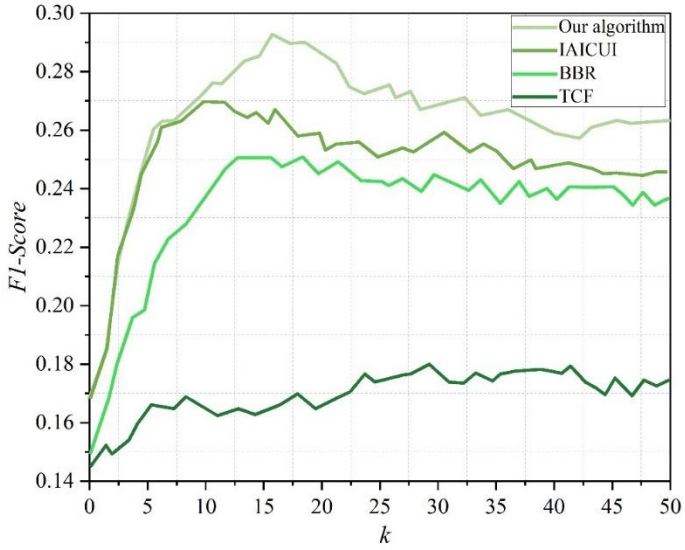


*Figure 4: Comparison of F1-Score of Four Algorithms under Different k Values*

The average values of each evaluation index of the four algorithms are shown in Table 1. It can be seen from the analysis that compared with IAICUI algorithm, BBR algorithm and TCF algorithm, the accuracy of this paper's algorithm has been improved by 8.64%, 14.31% and 42.32% on average, the recall has been improved by 2.97%, 15.16% and 65.83% on average, and the F1-Score has been improved by 11.20%, 12.54% and 50.37% on average. Based on the above analysis, it can be seen that the personalized learning resource recommendation algorithm proposed in this paper has better recommendation performance and stability, and is an effective and feasible recommendation algorithm.

*Table 1: The average values of the evaluation indicators for the four algorithms*

| Algorithm | Precision | Recall | F1-Score |
|---|---|---|---|
| TCF | 0.2722 | 0.1232 | 0.1743 |
| BBR | 0.3389 | 0.1774 | 0.2329 |
| IAICUI | 0.3566 | 0.1984 | 0.2357 |
| Our algorithm | 0.3874 | 0.2043 | 0.2621 |

## 2.4 Adaptive real-time interactive platform construction

### 2.4.1 Platform architecture

DM_Edu platform combines big data analysis and recommendation algorithms, not only realizes the functions of traditional education platforms, but also provides users with intelligent teaching services.The system architecture of DM_Edu platform is divided into the following three layers: (1) Resource layer is mainly used for storing various resources on the platform, including teachers' learning resources and students' data.

(1) The resource layer is mainly used to store various resources on the platform, including teachers' teaching resources, students' learning resources and user data.

(2) The management layer is mainly for the management of different applications of DM_Edu platform, including user management, resource management, security management, and so on.

(3) The Intelligence Layer is designed to realize personalized education and is the engine of the platform's intelligence and personalization. The platform builds the basic information for

user behavior tracking and analysis by recording the data of users using DM_Edu platform.

### 2.4.2 Platform functional modules

Based on the above system architecture, the core functions of DM_Edu platform are divided into teaching module, learning module, management module, and intelligent auxiliary learning module.The functional module design of DM_Edu platform is shown in Figure 5.

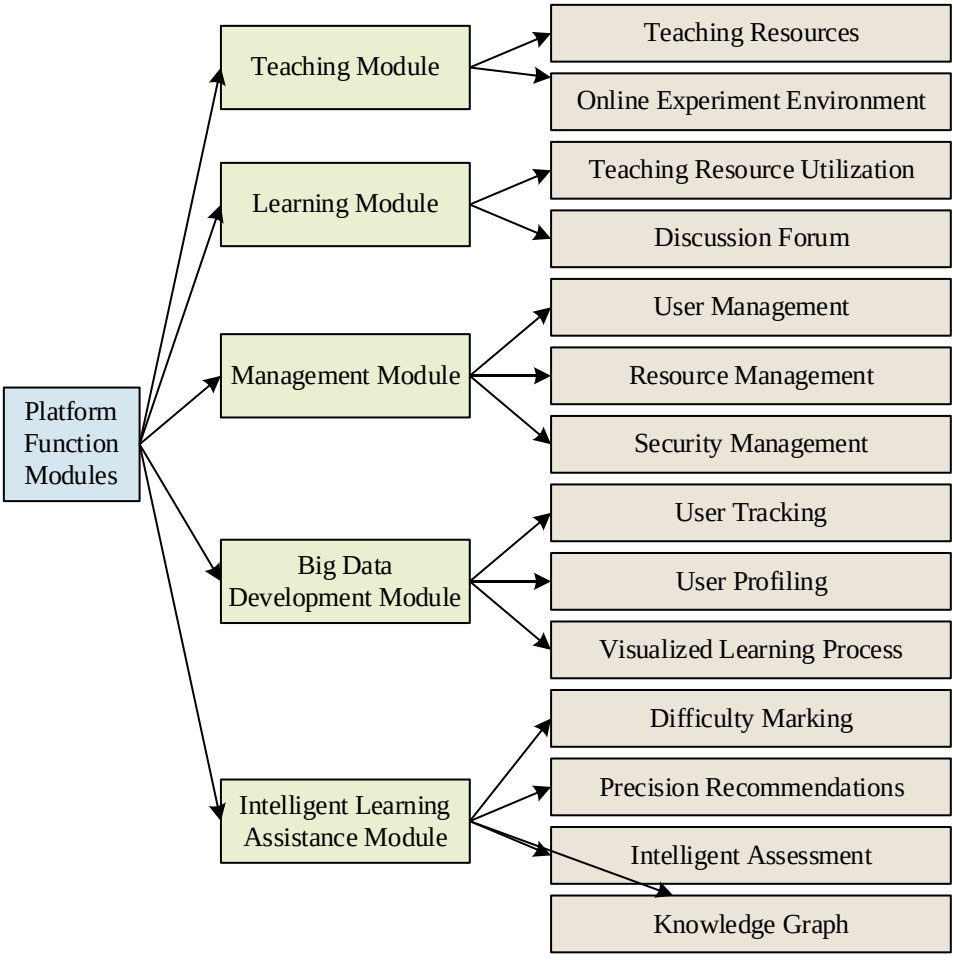


*Figure 5: The Functional Design of DM_Edu Platform*

(1) The teaching module is designed for the use of teaching data mining courses in colleges and universities, including teaching resources and online experimental environments.

(2) The learning module is mainly provided for students to learn relevant technologies in the field of data mining independently. With the help of this module, students who take the course can either study independently according to the teaching resources provided by the teacher or use the online experimental environment of the platform to complete the assignments set by the teacher.

(3) Management module. In order to facilitate the allocation of platform resources and safety management by the operation and maintenance team, the module develops three major management functions, such as user management, resource management and safety management, to realize the efficient management of the platform.

(4) Big Data Analysis Module collects user behavioral data on the platform and performs behavioral modeling using text mining, cluster analysis and other algorithms in order to build user profiles to help users self-assess, understand and improve. The module includes three

functions such as user tracking, user profiling and visualizing the learning process. The user's behavior is classified into six types: participation, persistence, concentration, interaction, academic challenge, and self-monitoring of learning. The online learning behavior analysis framework is shown in Table 2.

*Table 2: Online Learning Behavior Analysis Framework*

| Type of behavioral investment | Indicator example |
|---|---|
| Partake | Total login attempts |
| | Average online time |
| | Total page views |
| Interactive | Total replies to the teacher's post |
| | Total number of times you replied to a friend's post |
| | Number of replies received from peers |
| Persistence | Number of played course videos / Total course videos |
| | Maintain high weekly page views |
| Concentrate one's attention on | Time spent on individual tasks |
| | Total video playback times |
| Academic challenge | Difficulty Selection of Course Tasks |
| | Course search tool usage |
| Self-monitoring in Learning | Total page views for the course guide |
| | Average course task completion rate |

(5) Intelligent assisted learning module. Learners can mark knowledge difficulties. When users browse the courseware, they can mark the difficult points and present the results to the teacher's end, enabling the teacher to better understand the students' level of understanding of the course's knowledge points, so that he or she can explain the difficult points in the classroom and promote the students' understanding.

# 3 Analysis of the effect of the application of mobile systems in physical education

## 3.1 Research Objects and Tools

This study takes the dilemma influencing factors and cracking path of teacher-student interaction in junior high school physical education classroom as the research object.IFIAS Interaction Analysis System is a quantitative statistical tool, and its main purpose is to analyze the text and video dialogues. The system mainly analyzes the classroom video from three major aspects, from the teacher's language, student's language and classroom silence, which can be a more comprehensive analysis of the classroom teacher-student speech and behavior interaction. In the application method, IFIAS Interaction Analysis System adopts the sampling method of FIAS. In this system, the video is sampled with time card points, coded once with three seconds of time, and proceeded sequentially, recording the coding one by one, and finally forming the coding of the behavior of a class within a specified time. The research in this thesis mainly applies this analysis system to code the teacher-student interactions in the selected videos of physical education classes, and analyze the indicators according to the results of the coding situation, so as to bring instrumental support for the study of the current situation of teacher-student interactions in junior high school physical education classrooms.The IFIAS coding classifications and analyses are shown in Table 3.

*Table 3: IFIAS Coding Classification and Analysis*

| Classify | | Code | Description | Content |
|---|---|---|---|---|
| Teacher Language | Indirect effects | 1 | Receive emotions | Teachers express emotions autonomously, or they accept, clarify, or articulate students' feelings without resorting to threats. |
| | | 2 | Encouragement and Praise | Praise or encourage the student's behavior, and avoid jokes that may harm others. |
| | | 3 | Accept suggestions | Affirm the student's statement; repeat, expand, or develop the student's opinion or idea. |
| | | 4.1 | Pose open-ended questions | Ask students questions based on the teacher's opinions or ideas, or pose questions in a playful manner, and expect their responses. |
| | | 4.2 | Formulate closed questions | |
| | Direct influence | 5 | Lecture | Teachers provide facts or insights about the teaching content or steps, express their own views, or quote authoritative scholars' opinions. |
| | | 6 | Present | Issue commands that students can follow, expecting them to execute. |
| | | 7 | Criticism or upholding of authority | Using harsh language to alter students' behavior into acceptable patterns, scolding them, assigning blame, or outright dismissing their viewpoints. |
| Student speech | Student response | 8 | Benefit of passive response | Students are limited in their ability to freely express their thoughts when responding to teachers' questions or instructions. |
| | | 9.1 | Active response | Students actively express their emotions and attitudes toward the teacher's behavior; freely articulate their perspectives or ideas; respond beyond the expected answers, share their viewpoints, and proactively use body language to engage with the teacher. |
| | | 9.2 | Ask questions proactively | Take the initiative to ask questions and freely express your opinions. |
| | | 10 | Discuss with a peer | Students discuss and exchange ideas with peers |
| Silence or chaos | Indirect effects | 11 | The chaos that does not contribute to teaching | The classroom is in a state of disarray that does not contribute to teaching. |
| | | 12 | The Silence That Benefits Teaching | The student is in the thinking or practicing stage |
| Techno-logy | Direct influence | 13 | Teacher operation technology | Teachers use information technologies such as computers, tablets, slides, and projectors to conduct teaching activities. |
| | | 14 | User operation technique | Students participate in teaching activities through information technology. |

## 3.2 Holistic Analysis of Teacher-Student Interaction Characteristics in Physical Education Theory Classes

The ratios of teacher-student interaction behaviors in classrooms of different types of lesson examples are shown in Table 4, where 1~14 represent the codes of "emotion, encouragement, adoption, questioning, lecturing, instruction, criticism, passivity, initiative, discussion, confusion, silence, teaching and learning skills" respectively. In this paper, the physical education courses were categorized into "skill instruction, physical culture, and health education", and three examples were included under each category. The mean value of all the examples shows that code 4 accounts for 10.373%, code 5 accounts for 40.415%, code 9 accounts for 15.786%, and code 13 accounts for 13.248% in the classroom, all of which are more than 10%, which indicates that the teacher's questioning, lecturing, students' active response and teacher's manipulation of technology are the main links in the classroom of high school physical education theory class, and build up the basic skeleton of the classroom. Among them, the rate of lecturing reaches 40.41% indicating that the teacher in the classroom is still the dominant player in the classroom, which ensures the fullness of the classroom knowledge content and achieves the educational purpose of knowledge output and dissemination guidance.

*Table 4: Different Types of Class Examples and Teacher-student Interaction Behavior*

| Code | Mean | Skill Guidance | | | Sports and Culture | | | Health education category | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Lesson 1 | Lesson 2 | Lesson 3 | Lesson 4 | Lesson 5 | Lesson 6 | Lesson 7 | Lesson 8 | Lesson 9 |
| 1 | 1.403 | 0.716 | 0.959 | 1.381 | 2.714 | 0.26 | 1.921 | 2.279 | 1.612 | 0.787 |
| 2 | 1.554 | 0.362 | 3.25 | 3.231 | 0.682 | 0.131 | 0.901 | 0.616 | 3.216 | 1.594 |
| 3 | 3.195 | 2.638 | 4.806 | 5.191 | 2.823 | 2.24 | 2.561 | 2.488 | 2.601 | 3.403 |
| 4 | 10.373 | 10.454 | 13.601 | 10.961 | 9.032 | 10.033 | 7.807 | 16.915 | 5.941 | 8.613 |
| 5 | 40.415 | 68.153 | 48.376 | 28.84 | 39.16 | 59.231 | 24.072 | 35.891 | 29.212 | 30.8 |
| 6 | 2.334 | 0.603 | 1.683 | 2.536 | 2.031 | 1.449 | 5.255 | 0.522 | 4.207 | 2.72 |
| 7 | 0.041 | 0.246 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.122 | 0 |
| 8 | 3.674 | 3.37 | 0.722 | 0.578 | 1.35 | 0.789 | 15.112 | 3.009 | 5.2 | 2.938 |
| 9 | 15.786 | 10.098 | 10.828 | 18.109 | 12.983 | 6.073 | 16.135 | 19.499 | 29.205 | 19.144 |
| 10 | 5.829 | 1.8 | 0.006 | 9.23 | 4.176 | 0.001 | 12.29 | 3.841 | 10.022 | 11.098 |
| 11 | 0.248 | 0.12 | 0.122 | 0.233 | 0 | 0.794 | 0.009 | 0 | 0.621 | 0.332 |
| 12 | 1.804 | 0.486 | 2.051 | 1.963 | 1.131 | 2.369 | 3.458 | 1.449 | 0.5 | 2.833 |
| 13 | 13.248 | 0.967 | 13.594 | 17.762 | 23.019 | 16.62 | 10.5 | 13.489 | 7.547 | 15.736 |
| 14 | 0.101 | 0 | 0 | 0 | 0.904 | 0.001 | 0 | 0 | 0 | 0 |

## 3.3 Analysis of the results of visualization of teacher-student interaction in physical education theory classroom

In this paper, the interaction process of teachers and students in the physical education theory classroom is visualized and analyzed in four components: teacher's language, student's language, helpful silence and technology, taking the three types of courses, namely, skill instruction, physical culture and health education, of which lesson 1, lesson 4 and lesson 7, as an example.

### 3.3.1 Skills instruction classes

The dynamic ratio of teacher-student interaction behavior in Lesson Case 1 is shown in Figure 6. It can be seen that the teacher's language in the classroom has always occupied a dominant position, the teacher's language floats above and below 80%, is the protagonist of the classroom

speech and grasp the dominance of the language throughout the whole process, through the observation of the link between the teacher and the student speech, it is found that when the teacher's speech ratio is high, the student's speech behavior will be reduced in inverse proportion, and the student's speech behavior is in the state of being suppressed. The figure represents the ratio of teacher-student speech in the time period, and the intersection of teacher-student speech indicates the conversion of teacher-student speech status and the handover of discourse. The teacher-student speech curve in Lesson Case 1 has only 2 intersection points, indicating that the frequency of teacher-student interaction is low in this lesson case, and the students' subject position is not reflected.

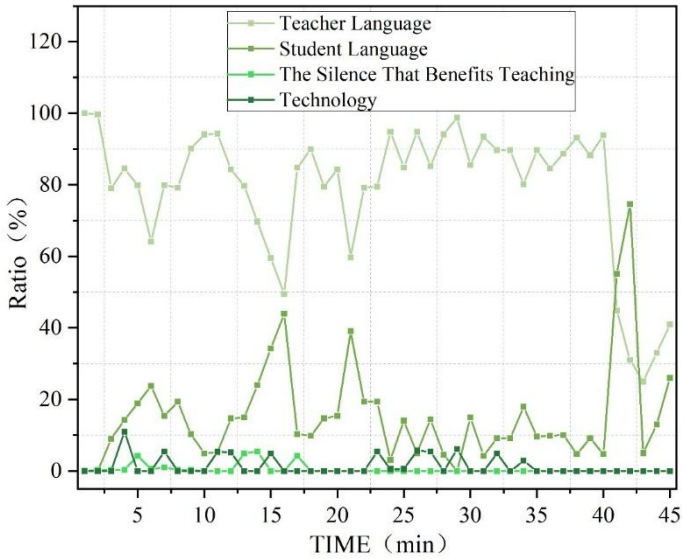


*Figure 6: Lesson 1: Dynamic Ratio of Teacher-Student Interaction Behavior*

### 3.3.2 Physical culture classes

The dynamic ratio of teacher-student interaction behavior in lesson case 4 is shown in Figure 7. In the case of sports and culture, the proportion of teacher's language in the classroom in Case 4 fluctuates gently, while the proportion of student's language is relatively low, and there are even seven blank periods of student's language in the time when the proportion of teacher's language is high, which means that the student's verbal behaviors are completely suppressed during this period, and the teacher continues to output the contents of the teaching. However, there are peaks of “student speech” after both the high-energy output of “teacher speech” and the prolonged “technology manipulation”, and by comparing the videos of the relevant time periods. The high rate of “technology” is due to the fact that the teacher played a video clip related to physical education, in which both teachers and students were immersed without verbal behavior, and after the video was over, there was teacher-student interaction, in which the teacher put forward highly subjective questions to further lead students to diverge their thinking and prompted them to take the initiative to speak, which shows that the teacher paid more attention to students' understanding of knowledge and focused on students' subjective behavior. The teacher's focus on the students' understanding and their subjective views.

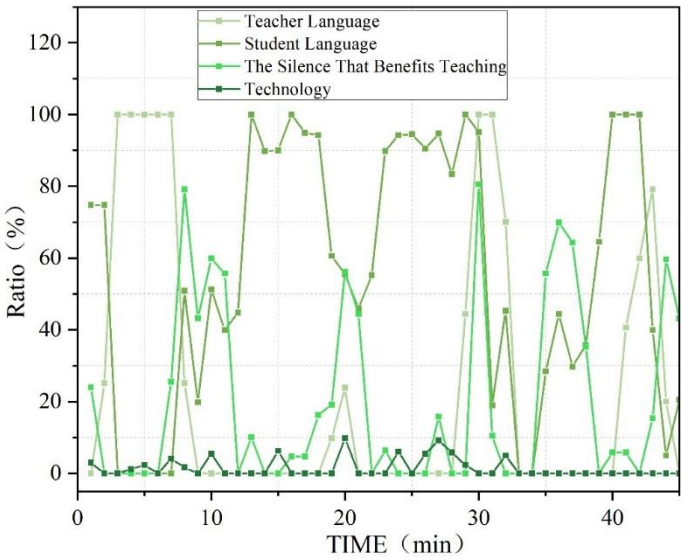


*Figure 7: Lesson 4: Dynamic Ratio of Teacher-Student Interaction Behavior*

### 3.3.3 Health education classes

The dynamic ratio of teacher-student interaction behavior in Lesson Case 7 is shown in Figure 8. It can be seen that the teacher's speech in the vast majority of cases in Lesson Case 7 is above the students' speech curve, indicating that the teacher is always in the dominant position of the classroom language in all time periods, but it can be seen that the students have speech behaviors in the vast majority of time periods, and there is a clear and brief handover of the language power only at minutes 7-8 and 25-26, which is the time of the group discussion as observed through the video. In terms of teacher-student verbal behavior, it can be seen that the teacher in the whole class in the time period up to 92% of the share, and student language only in the 42-44 minutes of the blank period, which fully demonstrates that although the teacher grasps the main discourse in the classroom, but also did not ignore the student's subjective position, and will frequently interact with the students.

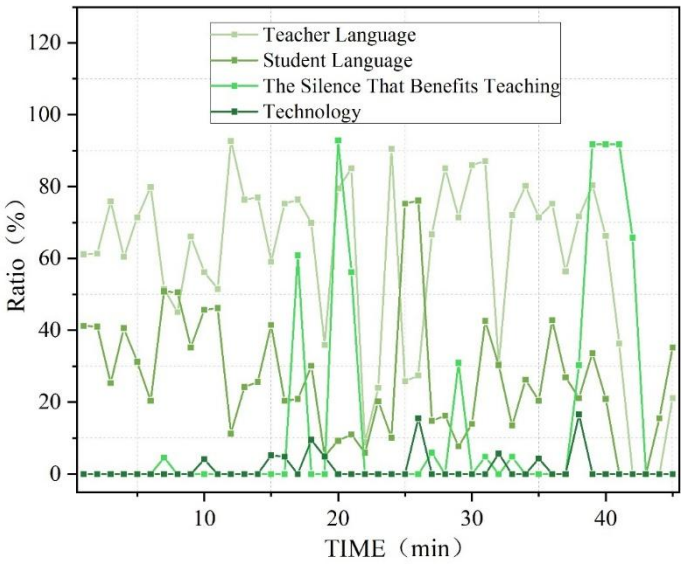


*Figure 8: Lesson 7: Dynamic Ratio of Teacher-Student Interaction Behavior*

### 3.4 Characteristics of Teacher-Student Interaction in Different Types of Physical Education Theory Classes

The characteristics of the teaching interaction structure of different types of sports theory classes are shown in Table 5. Skill instruction class belongs to the classroom with relatively strong knowledge, the teacher occupies the dominant position, and it is difficult to fully realize the students' main position. Physical culture classes are more literary and historical in nature, with a strong theoretical nature, and students know little about physical culture. Teachers' setting of interactive links and questions is unreasonable, leading to the state of teachers' “self-questioning” or continuous teaching and indoctrination. In the physical education and health classroom, teachers pay more attention to the expression of students' subjective opinions, guide students to think deeply through life examples and common sense, and mobilize the classroom atmosphere can be used to stimulate students' creativity by grouping points, and drive the classroom interactive atmosphere.

*Table 5: The Interactive Characteristics of Different Sports Theory Courses*

| Lesson | Teacher Language | Student Language | The Silence That Benefits Teaching | Technology |
|---|---|---|---|---|
| Lesson 1 | 0.59 | 0.7 | 83.96 | 14.75 |
| Lesson 2 | 3.63 | 13.48 | 71.77 | 11.12 |
| Lesson 3 | 3.02 | 17.81 | 51.93 | 27.24 |
| Lesson 4 | 1.97 | 23.87 | 55.96 | 18.2 |
| Lesson 5 | 3.86 | 15.83 | 73.45 | 6.86 |
| Lesson 6 | 5.78 | 9.96 | 41.94 | 42.32 |
| Lesson 7 | 1.92 | 14.03 | 58.45 | 25.6 |
| Lesson 8 | 2.27 | 7.52 | 46.33 | 43.88 |
| Lesson 9 | 3.83 | 16.17 | 47.12 | 32.88 |

# 4 Conclusion

This paper first proposes a collaborative filtering recommendation algorithm to realize the classification of similar learning groups, and then proposes a learning resource recommendation model on the basis of learners and learning resources to formulate suitable learning programs for learners; finally, a real-time interactive online learning platform with adaptive learning environment is constructed to realize the application of physical education in the mobile system again. The results are as follows:

(1) The personalized learning resource recommendation algorithm proposed in this paper the algorithm in this paper has better recommendation performance and stability, and its accuracy, recall and F1-Score are 42.32%, 65.83% and 50.37% higher than the traditional TCF algorithm, which is an effective and feasible recommendation algorithm.

(2) Using the interactive teaching platform, it was found that there were significant differences between teacher-student interactions in different physical education classrooms, with a large proportion of teacher's classroom speech and less teacher-student verbal interactions in skill instruction theory classes, while teacher-student interactions were more frequent in health education theory classes.

(3) Overall, the current physical education classroom teacher-student interaction content design is stereotypical, teacher-student interaction is too task-oriented, and the physical education classroom environment cannot provide sufficient protection. Therefore, to realize

effective teacher-student interaction in physical education classrooms, teachers and students need to complete teaching tasks together in a harmonious atmosphere, adjust the dominant position of teachers in the classroom, and strengthen the cultivation of students' sense of autonomy.

# About the Author

Ping Xie, female, Lecturer, Communist Party of China (CPC) Member, a native of Longxi County, Gansu Province. She graduated with a bachelor's degree in Physical Education from Xi'an Physical Education University and obtained a master's degree from the School of Physical Education and Sports, Beijing Normal University. Currently, she works as a full-time physical education teacher at Hunan Mass Media Vocational and Technical College. She has presided over one provincial-level teaching and research reform project and two department-level projects, and has published more than ten teaching reform and scientific research papers. Her main research and teaching focus on cheerleading, badminton and other sports courses. She holds the qualifications of National Level 1 Cheerleading Referee and National Level 1 Cheerleading Social Instructor. In recent years, she has served as a cheerleading referee and guided students to participate in sports competitions, winning first prizes in individual events and group events.

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