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CONSTRUCTION AND APPLICATION OF PHYSICAL EDUCATION CLASSROOM TEACHING MODEL INTEGRATING MOOC AND FLIPPED CLASSROOM

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Abstract. In terms of sports itself, mastering certain skills is a reliable way to avoid injury and futile training, and the teaching process needs to focus on imparting skills. Therefore, in order to optimize the teaching mode of physical education courses, this study explores the current improvement achievements and draws on the advancement of curriculum reform. The study proposes a recommendation method based on knowledge points and student characteristics by studying the characteristics and importance of sports techniques, in order to achieve high-quality customized content recommendations. Through validation experiments, the effectiveness of this recommendation method and optimization path is demonstrated. This study adopts an empirical research design to explore the impact of recommendation methods based on knowledge points and student characteristics on the teaching effectiveness of physical education courses. The effectiveness of this recommendation method is evaluated by collecting and analyzing students' learning data. Statistical analysis methods are used to analyze experimental data, including calculating the percentage of improvement in students' technical movements under different teaching modes. The research results indicated that recommendation methods based on knowledge points and student characteristics were of great significance for optimizing the teaching mode of physical education courses. The improvement of subjects' technical movements such as hitting and swinging in the new teaching mode was significantly better than that in the traditional teaching mode, with an increase of 10-20 technical movements per unit time, with a growth rate of over 20%. Compared with traditional teaching models, this teaching model has been subjectively recognized by students and has positive reference significance for the current physical education teaching model.

Key words: MOOC; Flipped classroom; Physical education; Tennis; Recommendation model

1. Introduction. Physical exercise requires a certain level of skill preparation. Taking tennis as an example, the swing, grip, and power of the racket all affect the effectiveness of hitting the ball [1]. However, students often find it difficult to master these skills on their own, so corresponding teaching guidance is needed to help correct the lack of skills [2]. The current physical education curriculum mostly adopts a demonstration imitation teaching mechanism, which makes it difficult for students to truly understand the essence of skills. Therefore, it is very necessary to carry out the reform of the physical education curriculum. Like other subjects, the idea of transferring the dominance of the education process from teachers to students coincides with Flipped classroom [3]. In the Flipped classroom, teachers help students, not just transfer information, but students are responsible for their own learning process and must control their own learning progress [4]. At the same time, modern educational technology, represented by MOOC, not only brings convenience to physical education teachers, but also broadens students' horizons. Therefore, combining physical education with modern educational technology to explore a new classroom model that is closer to the laws of education [5]. The research will explore the feasibility of the new classroom model from the perspective of integrating Flipped classroom and MOOC, and design a recommendation model with logical consistency in consideration of students' preferences to promote the reform of physical education. Our research will provide important references for the reform of physical education curriculum.

2. Related Works.

2.1. Application of MOOC. MOOC is widely used in various disciplines because of their massive open course resources, and their development and application are promoted in both directions by the real needs. Deng R et al. combed through the progress of MOOCs to propose optimization paths and analyzed these MOOCs through Biggs' 3P teaching and learning model framework, and they found that users mostly focused on the improvement of teaching and learning content, with little attention to learners and the interaction between the two, but rarely on the learners and the interaction between them [6]. Deng R's team then conducted

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a multidimensional study of the learner profile, categorizing them into behavioral, cognitive, affective, and social engagement components of MOOC learner evaluation, and the results showed that there were significant differences in the learners' factors and learning outcomes, which could help in subsequent instructional interventions [7]. Thus, a well-established English online teaching environment was constructed with knowledge partitioning in a multimedia, multi-resource context. In the modularized online environment, students were able to learn according to their characteristics and pace, and the results showed that this attempt could promote the efficiency of conversion of students' knowledge and stimulate their desire to learn, thus improving English learning [8].

2.2. Application of Flipped classroom. The flipped classroom as a constructivist teaching strategy fit is also receiving attention at all stages of education, Wei and other scholars introduced flipped classrooms into K-12 education, building on the existing progress of flipped classrooms for mathematics-based learning, where students previewed and took notes at home before the course began and formal classroom discussions about the notes took place. The experimental results showed that this attempt significantly improved the math performance of secondary school students, with a particularly significant improvement for students at the intermediate achievement level [20]. Jdaitawi explored the self-regulation and social impact of students in the flipped classroom, tested by comparing experimental embodiments, and the results of the analysis based on ANOVA analysis showed that students in the flipped classroom showed better self-regulation and social connectedness, which is an aid to self-directed learning [10].

2.3. Research on Physical Education Teaching. In the context of increasing technological development, physical education at home and abroad is also evolving with the times, and new evaluation methods and teaching techniques are bringing new changes to the physical education classroom. Zhang N, who specialized in technical optimization of basketball programs in physical education, regarded energy management as a key pedagogical objective in sports. To achieve this, Zhang developed a movement model based on Hidden Markov Models. This model enables the identification of approximate variables and unknown challenges, allowing for efficient energy utilization by athletes. [11]. De-kun et al. proposed a scheme to reverse the confusion in the traditional evaluation of physical education. The new algorithm constructed a BiLSTM model to rank and annotate the teaching tasks, then determined the weights of each indicator according to the intelligent optimal management factors to specify the quantitative evaluation scheme, and finally used a genetic algorithm for the optimal solution of the parameters. The results showed that the new evaluation method had a better performance than traditional methods and an advantage in terms of application time [12]. Forey's experimental team targeted the discussion of sports language to compensate for the lack of discussion of the course language, expanding the sports language capacity according to the linguistic theory and pedagogical methods provided by the system, and implementing the teaching with adequate preparation of the classroom language. The results of the analysis showed that explicit teaching of explicit language had a positive impact on students and teachers, and students' performance was improved, which proved that the language of instruction also had a considerable role in physical education [13]. Wang et al. scholars proposed improvements to the problem of too many factors in the evaluation of physical education, they believed that the problems of the evaluation system of physical education in colleges and universities should be analyzed before establishing an adaptive evaluation system. For this purpose, they introduced gray correlation analysis into the evaluation model, and the evaluation results under the concept of fuzzy mathematics also provided improvement strategies for this purpose [14].

2.4. Research Review. Scholars continue to move forward in their exploration of teaching models, during which new pedagogical concepts and technologies are used to address students' learning. This has led to more rational and efficient teaching and learning activities, but most of these reforms have been directed at classroom-based subjects and have not focused enough on the physical education curriculum. The goal of a physical education classroom is to cultivate students' athletic abilities and enhance their overall quality. However, in traditional physical education teaching models, students passively accept knowledge and find it difficult to fully improve their athletic abilities. The Flipped classroom introduces preview through information technology and multimedia tools, so that students can preview relevant skills through video, text, etc. before class. Students can apply this knowledge through practice in the classroom, and teachers can provide guidance and correction to promote the cultivation of practical sports abilities. In addition, Flipped classroom also increases the participation and interest of students. The use of multimedia tools can help improve students' understanding and mastery of skills and actions, and increase the effectiveness and interest of learning. To sum up, it is important and necessary to adopt the Flipped classroom model in the physical education class. Students' athletic abilities are cultivated through preview and practice; By increasing participation and interest, their active participation and comprehensive development are promoted. Therefore, it is very necessary to use the Flipped classroom in PE class. In light of this, the use of MOOC and flipped classrooms for physical education teaching improvement is in line with the current sense of direction of physical education curriculum reform, and the study will aim to advance this work and provide some help to this course that needs to be practiced.

3. Construction of physical education teaching model and evaluation system integrating MOOC and flipped classroom.

3.1. Construction of physical education teaching model integrating MOOC and flipped classroom. The realization path of the study is to integrate MOOC and flipped classrooms, apply this integrated teaching model to physical education teaching, and measure the feasibility of this model through effect evaluation. Therefore, MOOC and flipped classrooms need to be discussed in depth to explore their feasibility and integration nodes from the characteristics of educational psychology and physical education courses themselves. Compared with traditional cognitive learning, the Flipped classroom is favored by teachers and students at the same time, and has obtained good evaluation on teaching skills, learning flexibility, the effectiveness of teaching aids, student participation, and working environment [15]. The acquisition of sports in various dimensions is related to age and learning practice. Boys aged 8 to 9 need some practice to achieve positive growth, that is, in the process of physical education teaching, attention should be paid to the proportion of teaching methods and training [16]. Behaviorist teaching theory focuses on the construction of external stimuli, and environmental stimuli and learning methods determine the learning effect. The MOOC, with its massive and high level of external stimuli, can bring some improvement to physical education teaching. From the teaching side, such as teachers, students' learning data can be the basis for teaching according to their needs, and in the teaching design change machine can detect students' learning preferences to summarize more reasonable learning patterns. In addition, data-based learning summaries can also be used as a basis for analyzing changes in performance, visualizing and quantifying the causes of performance changes, and providing help for subsequent adaptive teaching, while sports correction based on individual differences is also one of the goals of physical education.

With the rich teaching resources, the optimization of the teaching mode can adapt to this change, while the interaction between the two can create more value-added space for learning efficiency. Traditional physical education is arranged at the beginning of the classroom, which tends to increase the time cost of students' learning and thus reduces their motivation, while the short classroom time cannot correct students' wrong exercise styles. This leads to a significant reduction in the effectiveness of physical education. The flipped classroom is an improvement of the teaching model, changing the traditional teacher-based model to a student-based model. This model makes reasonable use of time outside of class, allowing students more time and ways to prepare for what they are learning, while formal class time is spent correcting based on preparation. The teacher's identity in this model is no longer as a teaching leader but as a supporter or corrector; content such as textbooks and teaching aids is no longer the main vehicle for imparting knowledge but a reference material [17]. For physical education content, taking tennis or table tennis as examples, classroom teaching is conducted according to the model of teacher demonstration and student imitation. However, the teacher's mastery of skills is based on sufficient training and reasonable cognitive methods and levels, and simple demonstration is difficult for students to master the essentials of each movement skill, which is easy to cause a rigid situation. The flipped classroom is a constructivist approach that emphasizes that students are the main body of learning and that they accomplish their learning tasks through constructing the meaning of knowledge in a specific situation.

The study will use a constructed teaching model for the experiment, which consists of regular warm-up exercises and formal teaching tasks, with a tennis program chosen to teach forehand and backhand strokes and serves in one cycle of study. The curriculum needs to be designed holistically, with warm-up exercises related to the formal content, for example, a full-body workout to meet the running required to hit the ball,

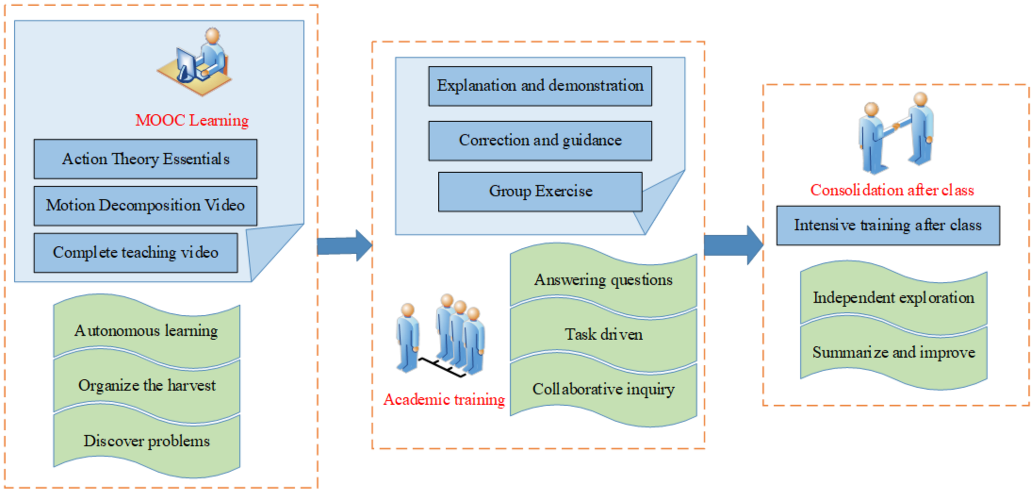


Fig. 3.1: Physical Education Teaching Mode Combining MOOC and Flipped Classroom

and upper-body warm-up as the focus during serve training [18]. At the same time, the course is conducted with the need to pay attention to the feedback of teaching information, implement the allocation of teaching percentages according to the actual situation, and advance teaching under dynamic principles. The specific teaching process is shown in Figure 3.1.

The teaching process as shown in Figure 3.1 consists of pre-course learning, classroom training, teacher instruction, and post-course consolidation. Before the start of the lesson, the teacher states the learning task and the learning points in the platform. In this part of the lesson, the teacher needs to propose the task arrangement according to the syllabus and provide the students with the learning path of each tennis movement, and then the teacher and students will agree to move to the next part of the lesson. The second half of the class will be summarized and evaluated to guide students to actively integrate what they have learned into their regular workouts. The whole teaching process will be recorded for the reference of other teachers and students on the platform.

3.2. MOOC-based knowledge sequence recommendation model. In the above-mentioned teaching process, teachers will recommend relevant courses for students to learn. Taking forehand hitting as an example, courses related to ground strokes, lead shots, and strokes will be recommended, but the sufficient number of related courses on the platform makes it difficult for students to choose, so a recommendation model based on knowledge sequences is needed to customize the recommended courses for students. The study will propose a recommendation model combining Heterogeneous Graph Attention Network (HAN) and Reinforcement Learning (RL), which can extract feature values from heterogeneous information and achieve continuous recommendations through reinforcement learning [19]. The structure of this model is shown in Figure 3.2.

The model structure as in Figure 3.2 contains three modules, which in logical order need to carry out heterogeneous network building based on user, course, and tennis knowledge after starting the operation, sampling of original paths by random wandering, and the sampling results will be used as input contents of the embedding module, after collecting students' knowledge preference feature vector by self-attention mechanism, and the contents collected from each path will be The content collected from each path will be expressed under the subsequent attention mechanism, and finally reach from user preference to knowledge point recommendation. The study will use the MOOC dataset to construct the information network, random wandering will sample all nodes for the training dataset, and the clicked knowledge points will be used as recommendation possibilities, assuming that there are A student users and a total of B sampled paths, random wandering sampling will get AxB paths, and the set of these paths will be set as N [20]. Since the node types in the network have

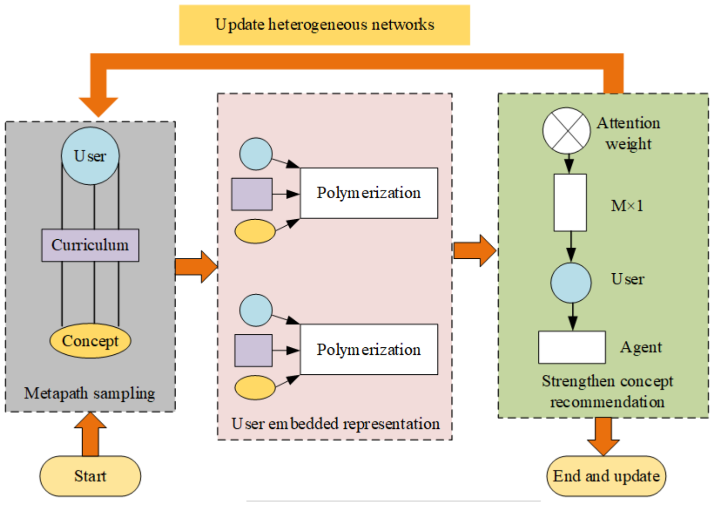


Fig. 3.2: Model structure of HAN-RL

heterogeneous characteristics, linear mapping is required for extraction. Suppose a node type is θ_i, and its type transfer matrix is M_θ, the mapping process is shown in equation 3.1.

$$E_i' = E_i.M_\theta \tag{3.1}$$

The E' and E_i of Equation 3.1 are the resultant feature values and the original feature values. Even for the same path, different nodes, their weights will be different, and then the self-attentive mechanism will be used to learn the weights of different types of nodes according to Equation 3.2.

$$\partial_{i,j}^{\phi} = \frac{exp[\sigma(a_\phi^T).[E_i'||E_j']]}{\sum_{k\in B_i^*} exp[\sigma(a_\phi^T).[E_i'||E_j']]} \tag{3.2}$$

The a_ϕ^T in Equation 3.2 represents the attention vector of the teacher user under the ϕ path, σ is the activation function, E_i' and E_j' represent the mapped feature vector and the mapped vector of the neighboring points after mapping, $||$ is the matrix splicing, k is the knowledge point, and $\partial_{i,j}^{\phi}$ is the weight coefficient of the two nodes i and j, whose magnitude depends on the feature because the neighboring points are different in the case of matrix splicing. i The meta-path embedding expression will be fused with the neighboring point weights as shown in equation 3.3

$$u_i^{\phi} = \sigma(\sum_{j\in N_i^{\phi}})\partial_{ij}^{\phi}.E_j' \tag{3.3}$$

In equation 3.3, u_i^{ϕ} is the meta-path embedding expression of i, according to this logic each node will be fused with its neighbors for embedding expression, and since the attention weights are generated through the unit path, it can learn all the feature information under that path. However, heterogeneous graphs have scale-free properties, so a multi-headed attention mechanism will be used for network training [21]. The node attention is replicated N times through the feature mapping and the final reflected value of the embedding expression vector as a user node is shown in equation 3.4.

$$U_i^{\phi} = \mathop{||}_{\mathrm{k=1}}^{\mathrm{K}} \sum_{j\in N_i^{\phi}})\partial_{ij}^{\phi}.E_j' \tag{3.4}$$

Equation 3.4 can be expressed by embedding the individual meta-path nodes of in the meta-path set $\phi_1, \phi_1, \ldots, \phi_M$ as $U_0, U_1, \ldots, U_M$. To get the embedding expressions of different students, for the M expression vector, the corresponding weight calculation can be generalized. The attention of the path layer can learn the deep semantic information of different types of heterogeneous data, and here the weights of different paths will be learned by a single layer. Let the interlayer vector be q, then the node embedding expressions under a single path can go through a nonlinear mapping and the interlayer vector does an inner product with the result, and the normalization of the weight result is as in equation 3.5.

$$\omega_{\phi i} = \frac{1}{|V|} \sum_{i \epsilon V} q^T.tan(W.u_i^{\phi}) + b \tag{3.5}$$

The V in equation 3.5 is based on the recommended videos in the MOOC heterogeneous network, and W and b are the learnable parameters and bias values. The weight coefficients are shared among different meta-path and path layer attention implementations as in Equation 3.6 using the softmax function to normalize the overall weights.

$$\beta\phi_i = \frac{\omega\phi_i}{\sum_{i=1}^{p} exp(\omega_{\phi i})} \tag{3.6}$$

The $\beta\phi_i$ in Equation 3.6 is the normalized meta-path feature expression vector and p is the specific meta-path node. It can be seen that the results are positively correlated with the value of the meta-path. The embedding expression of the weight coefficients will show different results depending on the path, so the embedding expression of the end-user area is as in Equation 3.7.

$$U = \sum_{i=1}^{p} \beta_{\phi i} U_{\phi i} \tag{3.7}$$

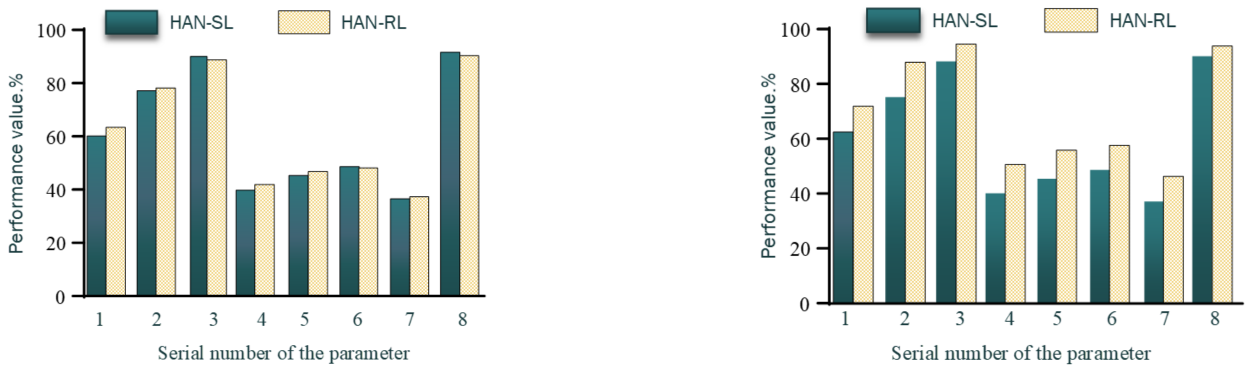
The conventional recommendation model is to establish a prediction mechanism to predict the error between the result and the true value by a loss function and to achieve the goal by reducing the error. However, this mechanism does not take into account that students' interests change over time and that the knowledge points that are extrapolated from the recommended content have a certain probability of becoming new interests of students, so the long-term interests of students need to be considered. The reinforcement approach of the study is to create an expectation reward mechanism as in equation 3.8.

$$\tau_{RL}(\theta) = E_{\pi ct|u} \sum_{t=1}^{T} r_t(ct|u) \tag{3.8}$$

The $\pi_\theta(c|u)$ in Equation 3.8 is the recommended strategy based on the knowledge of the current user uc_t, r is the even reward, and E is the expectation function. The state of the embedded expression as reinforcement learning under the optimal recommendation strategy enables the learning process to be applied to the system, while the new state is updated by modifying the heterogeneous network. To make the model more efficient, the study will be optimized using entropy normalization as in equation 3.9.

$$H(\pi_\theta(c|u)) = -\sum_{i=1}^{T} \sum_{ct_\epsilon C} log\left[\pi_\theta(ct|u_t).\pi_\theta(ct|ut)\right] \tag{3.9}$$

At this point, the model is constructed and optimized as described above. After considering and optimizing all aspects of the three modules, the model is able to achieve recommendations based on a sequence of knowledge points. This recommendation model allows students to extract their preferences over time as they learn each knowledge point of the tennis course, avoiding that the recommended content for subsequent MOOC courses is always related to the initial data sample.



(a) Overall knowledge recommendation performance

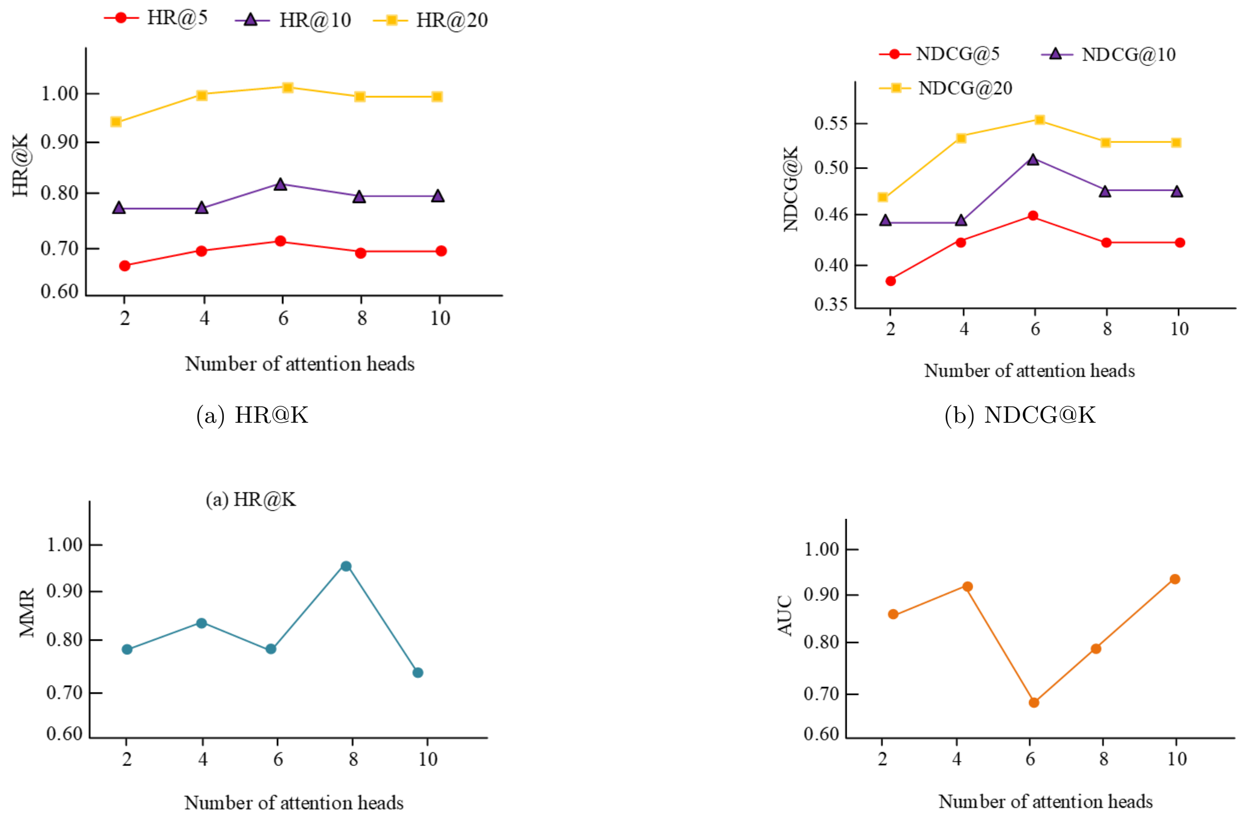
(b) Monomer knowledge recommendation performance

Fig. 4.1: Performance Comparison between Single Knowledge Point and Complete Set

4. Application of physical education teaching mode integrating MOOC and flipped classroom.. Before the start of the formal class, the constructed recommendation model will be simulated and trained to ensure the effectiveness of the recommendation model and its practical value for tennis lessons. The data on tennis teaching on the MOOC platform from September 1, 2018, to September 1, 2022, will be used here as the data set, of which 80% will be used as the training set and 20% as the reference set. Firstly, the accuracy of the constructed model is tested, and the constructed HAN-RL model and the group learning attention network model HAN-SL are added to the overall recommendation and single knowledge point recommendation training respectively, and the evaluation metrics are divided into four categories, which are: hit ratio of rank (Hit Ratio, HR), Normalized Discounted Cumulative Gain (NDCG) Cumulative Gain (NDCG), Means Reciprocal Rank (MRR), and AUC (Area Under Curve, AUC). The specific test parameters 1-8 represent: HR@5, HR@10, HR@20, NDCG@5, NDCG@10, NDCG@20, MRR, and AUC, respectively. the results are shown in Figure 4.1.

As shown in the test results in Figure 4.1, the data set is more concentrated because the course is limited to tennis lessons. The set cut and hyperparameter verification show that both group learning and reinforcement learning performance can reach a certain level, and the parameters of both models have their own strengths in overall learning. However, the reinforcement learning constructed by the study is better in single knowledge point learning and fully satisfies the accuracy requirements of the recommended model. The optimal parameter settings of the model are explored here to better recommend instructional videos for students on MOOC platforms. The recommendation hit rate of the model is examined, where the number of heads in the attention mechanism affects the students' embedded expressions. Therefore, the number of heads is set separately to obtain the relationship with the parameter growth, and the above parameters are introduced into the performance evaluation. The results are shown in Figure 4.2.

From the results in Figure 4.2, the growth of the HR evaluation parameter does not change much under different numbers of attention heads, which indicates that the correlation between the hit rate of the rank and the number of attention heads is not significant. The change of NDCG is highly correlated with the number of attention heads, and the overall trend is characterized by increasing and then decreasing, with a peak at the number of attention heads of 6, which means that the cumulative gain will be the highest and the recommended effect of the model will be the highest under this condition. The trend of MMR is similar to that of NDCG, and the best effect is reached when the number of attention heads is 8. The AUC evaluation parameter is decreasing and then increasing, and the lowest parameter value of the model is reached when the number of heads is 6, and 10 is the peak. In summary, each parameter generally reaches the optimal value when the number of heads is 6. Since increasing the number of heads leads to a decrease in the convergence rate, the optimal value is



(a) HR@K
(b) NDCG@K
(c) MMR
(d) AUC

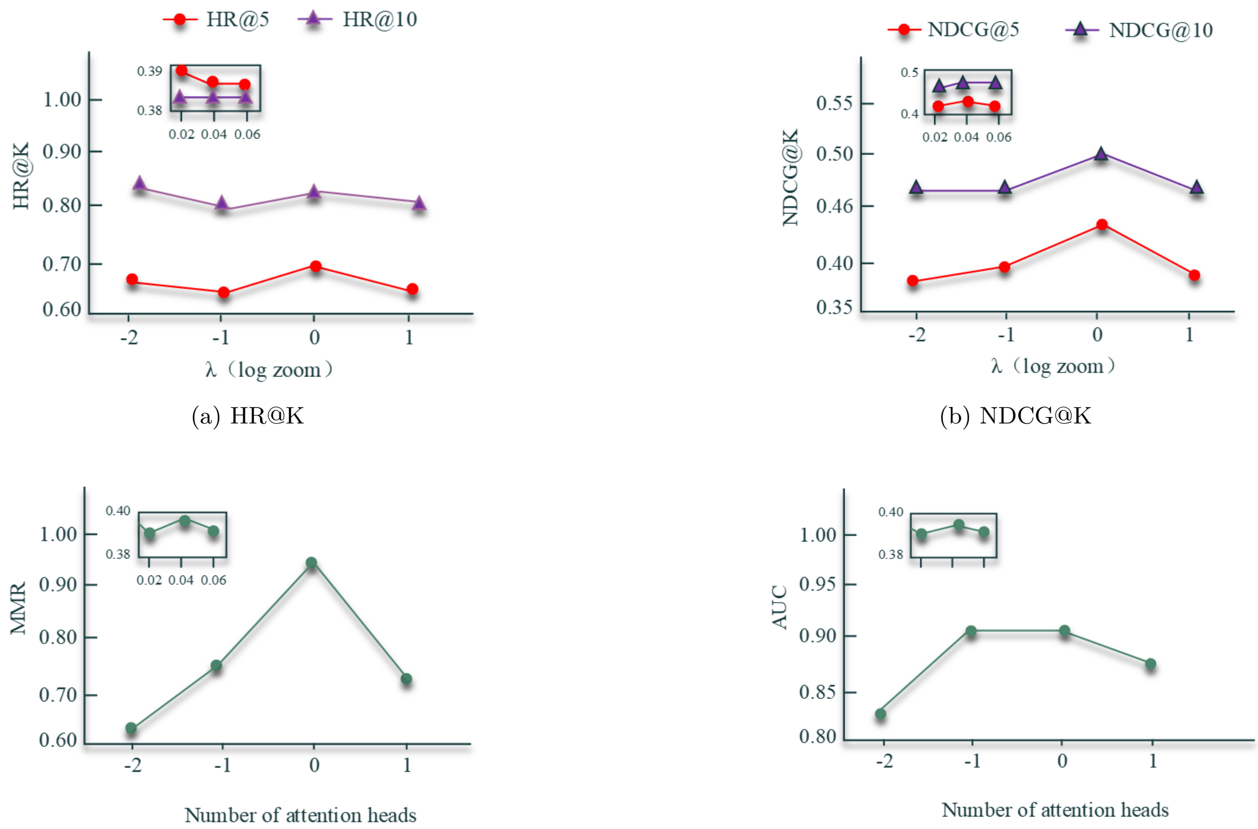
Fig. 4.2: Note the relationship between the number of headers and the parameters

chosen to be 6. The optimal value of the regularization coefficient will then be proposed for exploration, and the results are shown in Figure 4.3

From the results in Figure 4.3, although this coefficient has little effect on the weights, its variation is positively correlated with the performance metrics and is difficult to control, so this coefficient has some importance and therefore needs to be introduced in the recommendation model. After the MOOC-based recommendation model is prepared, the course experiment will be formally started. Two classes taught by Ms. M will be selected as the experimental group (n=51) and the control group (n=59), and two modes of instruction will be implemented, i.e., the experimental group will adopt the study-constructed instructional model and the control group will adopt the traditional instructional model for a semester-long course of 14 sessions, which will focus on tennis serve reception. With the exclusion of interference at the instructional level, the initial situation of the students will be understood to exclude the interference caused by their own situation. The results are shown in Table 4.1.

As per Table 4.1, it can be seen that the differences in students' scores on various tests before the start of the course were not significant ($p > 0.05$), which indicates that the interference of student factors can be eliminated. The course consisted of two parts, one of which was physical training and the other was skill practice. After half a semester, the physical fitness of the two classes changed, and the specific growth rates are shown in Table 4.2.

The comparison of the situations in Table 2 shows that there is little difference in the physical fitness of



(a) HR@K (b) NDCG@K

(c) MMR (d) AUC

Fig. 4.3: Relationship between λ coefficient and recommended performance

Table 4.1: Students' Mastery of Tennis Knowledge

Teaching Project	Experience Group	Control Group	t	P
Wave within 1 minute (p_1)	40.12 ± 3.21	39.33 ± 2.97	0.435	> 0.05
Shoot the ball in 1 minute (p_2)	15.46 ± 2.15	16.74 ± 1.63	1.321	> 0.05
Forehand stroke in 5 minutes (p_3)	19.21 ± 2.87	17.79 ± 2.73	0.637	> 0.05
Backhand within 5 minutes (p_4)	15.14 ± 2.51	14.23 ± 2.55	1.056	> 0.05
Serve within 3 minutes (p_5)	11.51 ± 1.85	13.16 ± 1.54	0.867	> 0.05
Rebound ball in 3 minutes (p_6)	18.25 ± 2.41	17.53 ± 2.07	0.513	> 0.05

the students before and after the course, which both exclude the interference caused by physical fitness factors to learning. It also shows that physical fitness training is used as a basic class for some time to prepare for the follow-up, and it is not an evaluation subject in itself. Subsequently, the two classes were tested separately at midterm, and the assessment results of each item were reflected as shown in Figure 4.4.

The midterm test scores are shown in Figure 4.4, and the scores of each item have improved compared to the beginning of the course. Comparing the performance of each item in both groups, it can be seen that the experimental group outperformed the control group in all items, and the difference was significant ($p < 0.05$). In

Table 4.2: Physical Fitness Changes of the Two Groups Before and After the Experiment

Teaching Project	Time of Test	Experience Group	Control Group	t	P
50-meter dash	Before the Course	7.49 ± 0.517	7.52 ± 0.539	-0.169	> 0.05
	Interim Test	7.33 ± 0.621	7.42 ± 0.544	-0.413	< 0.05
1000 meter run	Before the Course	253.51 ± 27.517	257.84 ± 29.972	-0.479	> 0.05
	Interim Test	242.33 ± 24.173	258.84 ± 30.251	0.431	> 0.05
Pull up	Before the Course	4.97 ± 3.703	4.58 ± 2.613	-0.482	> 0.05
	Interim Test	6.12 ± 3.241	5.36 ± 3.695	0.421	> 0.05
Turnaround run	Before the Course	18.72 ± 2.251	19.33 ± 2.873	-0.162	> 0.05
	Interim Test	18.07 ± 3.617	18.23 ± 2.34	-0.03	> 0.05

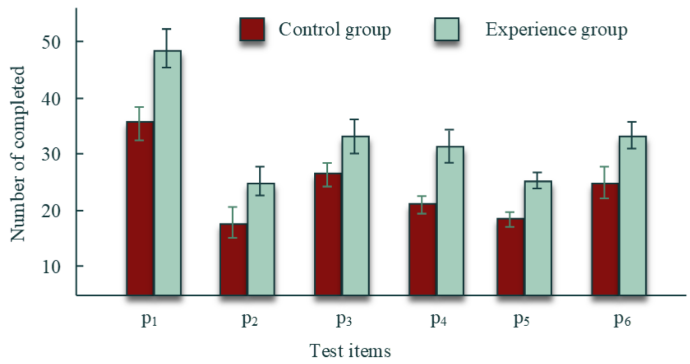


Fig. 4.4: Comparison of interim test results

tennis, the use of skills is closely related to the success of the project, and it is difficult to replace the instruction of skills with repetitive training alone, so the course recommendation based on the MOOC recommendation model will capture the characteristics of the students and make the effect twice as effective through the teaching of skills. After the midterm, the instructor will provide personalized instruction based on the problems that arise and determine the follow-up teaching plan, and the final results after intensive teaching are shown in Figure 4.5.

According to the results in Figure 4.5, it can be seen that the final scores of the experimental group were still better than those of the control group. Compared with the midterm, the scores of both groups have improved to a certain extent; the growth curve shows that the teaching model proposed in the study leads to consistently better growth in all test scores than the traditional teaching model, which indicates that the objective effect of MOOC integrated with flipped classroom meets the expectations. At this point, the students' subjective situation was used to understand the effect of the model, and their opinions were collected through the questionnaire method, and the results are shown in Figure 8, where the acceptance levels from 0-4 indicate: dislike, general attitude, basic acceptance, and very satisfied, respectively.

The results in Figure 4.6 show that the majority of students with acceptance levels of Basic Acceptance and Very Satisfied with the model, and the distribution and transformation of each grade level are similar, which indicates that the model has subjectively achieved the effect of satisfying students.

5. Conclusion. With the advancement of educational theory and technology reform, MOOC and flipped classrooms have long been richly explored experiences. The study uses these experiences in physical education to make the teaching model conform to the laws of the physical education curriculum. Since physical education courses require a lot of exercises to form muscle memory, proper skill instruction is the key to skill acquisition,

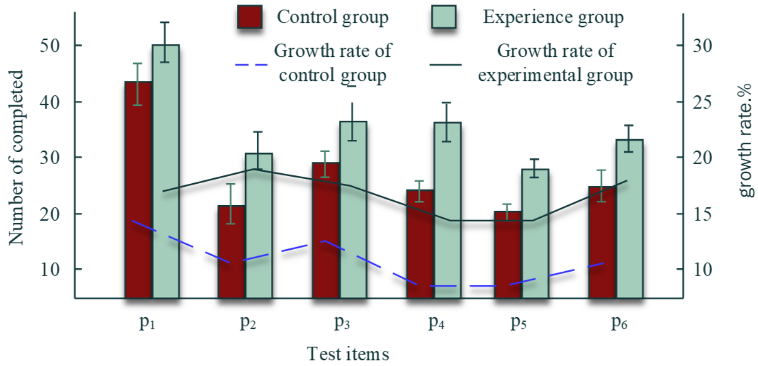


Fig. 4.5: Final result and change rate

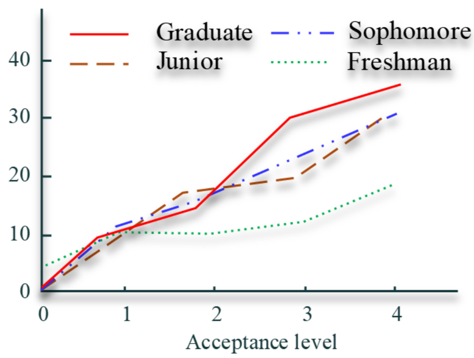


Fig. 4.6: Satisfaction of students of different grades with the new teaching model

and skill acquisition is closely related to individual students, so establishing a recommendation algorithm based on users and physical education courses is one of the focuses of the study. A recommendation method based on the sequence of knowledge points is formed through the attention mechanism and reinforcement learning, which can overcome the situation that students' interest points change due to the course progress, and the test proves that the parameters of this recommendation method can meet the automated recommendation of physical education courses. The new teaching model allowed students to improve their performance in a range of tennis training items, such as swing, by 20-30%, and each element showed a more significant improvement compared to the traditional teaching method ($p < 0.05$). Subjective findings showed that the majority of students in all grades in this elective physical education course had positive attitudes toward the instructional model. In the follow-up work, the study will advance teaching improvements in other skill-based sports courses to enrich and optimize the integration of MOOC and flipped classrooms.

REFERENCES

[1] Hewitt, M., Pill, S. & McDonald, R. Informing Game Sense Pedagogy with a Constraints-Led Perspective for Teaching Tennis in School. Ágora para la Educación Física y el Deporte. (2018)

[2] Zhao, D. & Kang, H. Practice exploration of the flipping classroom in a table tennis club in the informatization age. *Procedia Computer Science*. **166** pp. 175-179 (2020)

[3] Zhu, M., Sari, A. & Lee, M. A comprehensive systematic review of MOOC research: research techniques, topics, and trends

from 2009 to 2019. *Educational Technology Research And Development.* **68**, 1685-1710 (2020)
[4] Akçayır, G. & Classroom:, A. review of its advantages and challenges[J]. *Computers & Education.* **126** pp. 334-345 (2018)
[5] Fathi, J. & Rahimi, M. Examining the impact of flipped classroom on writing complexity, accuracy, and fluency: a case of EFL students. *Computer Assisted Language Learning.* **35**, 1668-1706 (2022)
[6] Deng, R., Benckendorff, P. & Gannaway, D. Progress and new directions for teaching and learning in MOOCs. *Computers & Education.* **129** pp. 48-60 (2019)
[7] Deng, R., Benckendorff, P. & Gannaway, D. Linking learner factors, teaching context, and engagement patterns with MOOC learning outcomes. *Journal Of Computer Assisted Learning.* **36**, 688-708 (2020)
[8] Zhang, N. Development and Application of an English Network Teaching System Based on MOOC. *International Journal Of Emerging Technologies In Learning.* **13**, 149-160 (2018)
[9] Mohammed, H. & Daham, H. Analytic hierarchy process for evaluating flipped classroom learning. *Computers, Materials & Continua.* **66**, 2229-2239 (2021)
[10] Wei, X., Cheng, I., Chen, N. & Others (2020) Effect of the flipped classroom on the mathematics performance of middle school students. *Educational Technology Research And Development.* **68**, 1461-1484 (0)
[11] Jdaitawi, M. The effect of flipped classroom strategy on students learning outcomes. *International Journal Of Instruction.* **12**, 665-680 (2019)
[12] Zhang, N., Han, Y., Crespo, R. & Others (2020) Physical education teaching for saving energy in basketball sports athletics using Hidden Markov and Motion Model. *Computational Intelligence.* **37**, 1125-1140 (0)
[13] De-kun, J. & Memon, F. Design of mobile intelligent evaluation algorithm in physical education teaching. *Mobile Networks And Applications.* **27**, 527-534 (2022)
[14] Forey, G. & Cheung, L. The benefits of explicit teaching of language for curriculum learning in the physical education classroom. *English For Specific Purposes.* **54** pp. 91-109 (2019)
[15] Ivashchenko, O., Iermakov, S. & Khudolii, O. Modeling: ratio between means of teaching and motor training in junior school physical education classe. *Pedagogy Of Physical Culture And Sports.* **25**, 194-201 (2021)
[16] Wang, Y., Sun, C. & Guo, Y. A multi-attribute fuzzy evaluation model for the teaching quality of physical education in colleges and its implementation strategies. *International Journal Of Emerging Technologies In Learning (iJET).* **16**, 159-172 (2021)
[17] Polat, H. & Karabatak, S. Effect of flipped classroom model on academic achievement, academic satisfaction and general belongingness. *Learning Environments Research.* **25**, 159-182 (2022)
[18] Chiu, Y., Clemente, F., Bezerra, P. & Others (2022) Day-to-day Variation of the Heart Rate, Heart Rate Variability, and Energy Expenditure during FIFA 11+ and Dynamic Warm-up Exercises. *Journal Of Human Kinetics.* **81**, 73-84 (0)
[19] Wang, Z., Liu, C. & Gombolay, M. Heterogeneous graph attention networks for scalable multi-robot scheduling with temporospatial constraints. *Autonomous Robots.* **46**, 249-268 (2022)
[20] Mei, G., Pan, L. & Liu, S. Heterogeneous graph embedding by aggregating meta-path and meta-structure through attention mechanism. *Neurocomputing.* **468** pp. 276-285 (2022)
[21] Brunke, L., Greeff, M., Hall, A. & Others (2022) Safe learning in robotics: from learning-based control to safe reinforcement learning. *Annual Review Of Control, Robotics, And Autonomous Systems.* **5** pp. 411-444 (0)

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