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Article

Research on Intelligent Integration of Civic and Political Elements in Physical Education Teaching and Personalized Learning Paths Supported by Educational Big Data

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Abstract: This paper focuses on the background of intelligent integration of Civics elements in sports teaching under the support of big data, constructs a knowledge map of sports professional course teaching that integrates Civics elements, builds a database of Civics instances with the goal of course Civics nurturing, and proposes a knowledge tracking method based on the Transformer on the basis of which comparative experiments are carried out in four public datasets. The ant colony algorithm is used to recommend the optimal learning path for sports-oriented learners, and the personalized recommendation for sports-oriented learners is designed and implemented, and the experimental group is selected to verify the applicability and accuracy of the recommendation method. The results show that the knowledge tracking method based on Transformer can better reflect the learners' mastery of knowledge points and can effectively improve the accuracy of the knowledge tracking task. Finally, through the learning path recommendation, the F1 values of the recommended paths are all above 0.6, which verifies the effectiveness, accuracy and adaptability of the algorithm.

Keywords: civics integration; knowledge tracking model; learning path recommendation; ant colony algorithm

1. Introduction

Teaching and educating people is the fundamental requirement of physical education teaching, in the context of “curriculum politics”, physical education should not only improve the physical quality of students, but also allow students to experience the fun of sports, the value and spirit of sports in the process of sports [1-4]. The essence of the sports program is “moral education and comprehensive development”. If physical education is to “cultivate talents”, and Civics education is to “cultivate personality”, then the Civics of Physical Education Program is to integrate the elements of cultivating students' personality, such as patriotism, value concepts, and the pursuit of life into the physical education disciplines [5-8], especially in the context of the wide application of big data in education, which is the most important factor in the development of the physical education curriculum. In the context of the era of the wide application of educational big data, the integration of the elements of the Civics and Politics of physical education teaching is of great significance for the overall development of students [9-10].

Educational big data refers to the collection, storage, analysis and utilization of a large amount of data generated by students, teachers and educational institutions through the means of informatization technology in the field of education, and the processing and analysis of such data through data mining, machine learning and other technological means, so as to realize personalized learning and improve the level of educational talent cultivation and management [11-15]. In the field of physical education, traditional physical education often relies on teachers' subjective judgment and experience, while educational big data can collect students' movement data through intelligent devices and sensors, and analyze and process these data [16-19]. By analyzing students' exercise volume, speed, endurance and other indicators, students' athletic ability and progress can be objectively assessed, providing teachers with a more accurate basis for teaching [20-22]. In addition, because each student's sports ability and interest are different, traditional classroom teaching often fails to meet the individual needs of each student, while education big data can develop personalized sports teaching plans based on students' sports data [23-26]. In the personalized learning brought about by education big data, through the integration of Civics and Politics elements, it can subconsciously and positively influence students' ideology, behavior, value beliefs, and life choices, thus promoting the overall development of students [27-30].

The importance of Civics and Politics in sports courses cannot be ignored, which can not only shape students' good psychological quality and moral character, but also help students establish a correct worldview, outlook on life and values. Literature [31] and literature [32] emphasize that the combination of physical education and ideological and political education plays an important role in cultivating students' moral quality and comprehensive quality, and point out the many problems faced by this combination of teaching and put forward coping strategies. Literature [33] based on literature review, questionnaire survey and other aspects, verified that the combination of ideological and political education and physical education program effectively improves the quality of students' physical education learning and the overall development of students' moral and physical qualities. Literature [34] discusses the implementation of ideological and political education in physical education classroom based on questionnaire survey, interviews and other methods, and believes that exploring the teaching concepts and teaching objectives in physical education in order to improve the penetration effect of moral education in physical education is of great significance for the reform of physical education. Literature [35] explored the construction path of the objectives, contents, teaching methods and teaching evaluation of university physical education courses from the perspective of “curriculum ideology”, based on the concept of Outcome-Based Education (OBE) and the principle of reverse design. Literature [36] used literature review and other methods to reveal the potential problems of public physical education courses, including the poor educational effect of the courses and the insufficient excavation of ideological and political content, etc., and put forward optimization paths, aiming to improve the teaching effect of ideological and political education in public physical education courses.

The application of educational big data in physical education not only transforms the traditional mode of physical education, but also provides students with personalized learning experience and improves teaching quality and efficiency. Literature [37] reviewed the scope of application and educational impact of digital intelligence technology (DIT) in physical education, and the results pointed out that DIT transformed the face of physical education and promoted its development towards intelligent and personalized teaching. Literature [38] showed through a questionnaire survey that the current university teachers are significantly deficient in the innovative training of students in physical education, emphasizing the necessity of the application of big data in physical education. Literature [39] constructed a big data analysis framework for sports behavior mining and personalized health services by analyzing users' sports data in order to find out the trend of users' cyclic exercise patterns and changes in exercise center rate, and the analysis results can be used for personalized medical services. Literature [40] introduced the background of sports big data, sports big data management, and methods of sports data analysis, and examined representative research topics in the field of sports big data, aiming to help researchers understand sports big data more comprehensively. Literature [41] emphasized that physical education can facilitate the reform of teaching methods through advanced teaching technologies such as big data, so as to provide students with better teaching experiences and learning needs. Literature [42] proposed an artificial intelligence-based physical education management system aimed at improving work efficiency and reducing the workload of physical education teachers, and verified the effectiveness of the system to effectively improve the efficiency and quality of physical education teachers' work. Literature [43] analyzes the problems that may arise in the process of college sports contextual teaching and the individualized needs of college students through the study of big data and precise physical education, and describes the methods of its thinking design and practical application.

This research constructs a teaching knowledge graph of physical education professional courses integrating ideological and political elements and proposes a method for knowledge tracking based on Transformer. This method optimizes the input processing of the self-attention operator layer to improve the prediction performance of the deep knowledge tracking model, achieving precise tracking of students' ideological and political knowledge level in physical education. Verify the model's performance by comparing it with multiple models on multiple datasets. Then according to the learner's personalized characteristics using ant colony algorithm to generate learning paths, selected 30 experimental subjects, divided into two groups on the performance of personalized learning path recommendation algorithm simulation experiments to verify the performance of the sports course Civics provides a theoretical basis and technical support for the innovative practice of sports courses.

2. Pedagogical Knowledge Mapping with Civics Elements

2.1. Construction of a Curriculum Civics Database for Physical Education Programs

According to the Guidelines for the Construction of Civics in Courses of Higher Education, the organization of the content of curriculum civics should be centered on ideals and beliefs, with love for the Party, patriotism, socialism, the people, and the collective as the main line, and systematic education around the focuses of family and national sentiments and cultural literacy.

Taking computer courses as an example, combining the characteristics of teacher education, the characteristics of computer specialties and the background of the artificial intelligence era, the framework of the Civics and Politics of Physical Education Specialty Courses and the knowledge points were sorted out to help establish a database. The featured civic and political contents include the following civic and political elements: scientific and technological power, educational power, craftsmanship, vocational ability and engineering ethics. The constructed Civics and Politics framework for the physical education program is shown in Figure 1, where the numbers connected in green indicate the number of subcategories that can be expanded in the module.

Figure 1. Ideological and political framework of sports major courses.

The sources of Civics and Politics examples are mainly considered to be famous quotes, celebrity stories or national events, with traceable sources, authentic data, and themes that are in line with the characteristics of college students. For each leaf node on the Civics framework of computer courses, 50 relevant Civics instances are manually completed, i.e., the first batch of database data is obtained, including Civics instances as well as their corresponding types, totaling 56 types of data.

2.2. Construction of Knowledge Graph

After constructing the database and importing the knowledge points in Physical Education and Health Care, it is then necessary to construct the knowledge points and Civics types as well as the associative relationships between individual knowledge points. For this purpose, we introduced the knowledge mapping technology to correlate the knowledge of different subject areas to help teachers better combine the elements of Civics with the knowledge of each subject area.

Logically, knowledge mapping is divided into a data layer and a schema layer. The data layer expresses facts, such as entities, attributes and attribute values, in ternary groups, which can be stored using databases such as Neo4j graphs. The schema layer standardizes the facts in the data layer through the ontology library, provides conceptual templates for knowledge storage, enhances the organization of the knowledge structure, and reduces data redundancy. Constructing the knowledge graph can be accomplished through knowledge extraction and knowledge fusion of the raw data.

Knowledge extraction generally includes three parts: entity extraction, relationship extraction and attribute extraction, which can be accomplished using ternary groups (entity 1, relationship and entity 2). Knowledge extraction is done manually and stored in the form of Neo4j graph database.

2.3. Access to Civics Elements

Focused web crawler, also known as topic web crawler. The technology starts crawling from the initial link, then evaluates and retains links related to the topic based on the analysis algorithm, puts them into the queue of links waiting to be crawled, marks them to prevent repeated crawling, and then acquires the links again through a certain search strategy until certain conditions are met.

In order to further improve the accuracy and efficiency of crawling, the clustering algorithm is introduced into the knowledge crawling process. The main links include: ① For the links to be crawled, a score F1 is given based on the analysis algorithm; ② Clustering of a certain number of crawled links and calculation of the similarity F2 between the links to be crawled and the crawled links; ③ Sorting of the links, and crawling of the links with higher scores. Up to this point, by specifying keywords, relevant data from online resources can be crawled as the initial material for the example of the Civics element.

3. Tracking the level of students' knowledge of sportsmanship

3.1. Inputs and outputs of the knowledge-tracking task

In this paper, we propose that the output of the model can be viewed as the probability of a particular student answering a given exercise ID correctly. The input to the model is the student's historical practice record, which includes the exercise ID, the answer result, and the skill ID to which the exercise belongs; the output of the model is the predicted value of the probability of answering a particular exercise correctly.

The model takes inputs from the beginning to the t th question for each student in the dataset during the training phase, so that the model outputs a prediction of the correct answer to the $t+1$ th question, and then optimizes the parameters of the model at the cost of comparing it with the actual result of the $t+1$ th question. The predicted values output from the trained model can be used as evaluation metrics and applied to assess the degree of skill mastery of students. The problem of concern for this model is to improve the accuracy of this prediction, i.e:

$$P\left(r_{t+1} \mid \left(e_0, s_0, r_0\right), \left(e_1, s_1, r_1\right), \cdots, \left(e_t, s_t, r_t\right), e_{t+1}\right) \tag{1}$$

where: e, s and r represent the topic ID, skill ID and result respectively.

3.2. Modeling framework

3.2.1. Embedded Representation

For the model inputs, an embedding representation of the elements in the sequence is required. There are a total of 3 types of embedding representation vectors. Let the currently processed student be i. For the k questions under this student ID, the 3 vector groups are vector group $\mathbf{E}_i$ converted from the sequence of question IDs, vector group $\mathbf{S}_i$ converted from the sequence of skill IDs, and vector group $\mathbf{R}_i$ converted from the sequence of answers, and there are k vectors in each group. The dimensions of each type of vectors need to be predefined, where the vector dimension of vector group $\mathbf{R}_i$ should be the sum of the dimensions of vectors $\mathbf{E}_i$ and $\mathbf{S}_i$, taking into account the subsequent gating operation.

The model presented in this paper uses an embedded representation layer with randomly initialized parameters. In particular, for the vectors in the set of response sequence vectors $\mathbf{R}_i$, a normally distributed parameter initialization method with different expectation values is set based on correctness or incorrectness, i.e., when the response is correct there is $\mu > 0$, and vice versa there is $\mu < 0$.

As an input to the self-attention module, $\mathbf{E}_i$ and $\mathbf{S}_i$ are processed by splicing according to the correspondence. Position encoding: sequence processing under the attention mechanism relies on position encoding to contain the position information of sequence elements. In this paper, the position encoding of the proposed model adopts an absolute position encoding method, i.e., the position encoding of the sine-cosine function. For length d and position p in the sequence, the value of dimension i in the position coding vector is:

$$\mathbf{E}_{pos,2i} = \sin\left(p/10000^{2i/d}\right)$$
$$\mathbf{E}_{pos,2i+1} = \cos\left(p/10000^{2i/d}\right) \tag{2}$$

This set of values forms the position coding vector. where $i \in \{0,1,2\cdots d_{model}/2\}$. After generating the position encoding it is merged with the embedding representation vector in an additive manner.

3.2.2. Resulting control gates

In order to be able to efficiently utilize the information in the result part of the practice record, this model employs a gate mechanism to handle the embedded representation of this part. Regarding the scoring mechanism in the attention operation, consider the case of a sequence in which there are two answers to a question under the same knowledge point: the case in which both answers are correct relative to the case in which one is correct and one is incorrect should get a larger value of the self-attention operation on the attention operation involving the question, thus contributing more to the prediction of the output being correct.

In previous knowledge tracking studies, for exercise IDs in practice records, there are n states for exercises of n classes of topics; when combining the states of results, considering the case where in general there are only right and wrong results, the record of any completed exercise is extended to $2n$ states.When coding practice records in DKT using a one-hot approach, a matrix of $2n$ -dimensional matrices are used in DKT, and even models that use embedded representations are usually directly extended to encode the number of states.

In order to optimize the computation under the embedded representation as well as the dot product attention mechanism, this model uses a gate mechanism instead of a simple expansion, i.e., for the input of the value ($\mathbf{V}$) part of the multi-head attention module, there are:

$$E_i^v = \left(\mathbf{E}_{e_i,s_i} + P_i\right) \odot \tanh\left(E_{r_i}\right) \tag{3}$$

where: $\mathbf{E}_{e_i,s_i}$ is the embedding representation vector of spliced topic and skill information, P_i is the positional encoding, E_{r_i} is the embedding representation of the result, and $\odot$ is the Hadamard product operation. Unlike the embedding representation of topic ID and skill ID, E_{r_i} does not need to be combined with positional encoding.

3.2.3. Multi-attention operations

The multi-head attention module is the core part of the encoder and decoder. This model uses a scaled dot product to compute the attention, i.e:

$$Attention(\mathbf{Q},\mathbf{K},\mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^{\mathrm{T}}}{\sqrt{d_k}}\right)\mathbf{V} \tag{4}$$

Usually the query, key and value in the self-attention operation are denoted by $\mathbf{Q},\mathbf{K}$ and $\mathbf{V}$, which come from the embedded representation vector of the topic information after performing the linear operation, respectively. Both Q and $\mathbf{K}$ come from the vectors obtained from further processing of the topic IDs and skill IDs, while $\mathbf{V}$ comes from the former after performing a gate operation on the resultant vectors, namely

$$\mathbf{Q}_i = \mathbf{W}_q\left(\mathbf{E}_{e_i,s_i} + P_i\right)$$
$$\mathbf{K}_i = \mathbf{W}_k\left(\mathbf{E}_{e_i,s_i} + P_i\right) \tag{5}$$
$$V_i = \mathbf{W}_v\mathbf{E}_i^v$$

where: $\mathbf{W}$ is a linear transformation matrix, this model uses 8 different sets of $\mathbf{W}$ to divide the input part into 8 heads to capture richer features mapped to multiple linear spaces. After computing the attention score using the self-attention mechanism, the score is multiplied in the form of coefficients with the vectors that have been subjected to gate transformation and linear operations, and the heads are spliced and merged, ultimately converting the input vectors of the individual elements into representations in the form of groups of vectors for each element in the sequence. The number of encoder and decoder blocks is set to 2, i.e., the self-attentive structure and the subsequent feedforward neural network structure are repeated twice. Its input to the second block of $\mathbf{Q}$, $\mathbf{K}, \mathbf{V}$ is a linear mapping of the output of the precursor feedforward neural network.

3.3. Student knowledge level tracking experiment

3.3.1. Evaluation indicators

This experiment evaluates the performance of the proposed method in terms of the area under the curve (AUC), which is the most commonly used evaluation metric in the field of knowledge tracking.The AUC is defined as the area under the receiver operating characteristic curve (ROC).The ROC curves are plotted on the basis of the confusion matrix, which is the most widely used and computationally simple of the metrics used in the classification problem. The confusion matrix is divided into four base metrics, which are:

(1) True Positive Example (TP): the learner answers correctly and the model predicts the result as a correct answer.

(2) False Positive Example (FP): the learner answers correctly and the model predicts the result as a correct answer.

(3) False positive example (FP): the learner answers incorrectly and the model predicts a correct answer.

(4) False Negative (FN): the learner answers incorrectly and the model predicts an incorrect response.

This leads to the true rate (TPR) and false positive rate (FPR):

$$
\begin{aligned}
TPR &= \frac{TP}{TP+FN} = \frac{TP}{P} \\
FPR &= \frac{FP}{FP+TN} = \frac{FP}{N}
\end{aligned}
\tag{6}
$$

The horizontal coordinate of the ROC curve is the FPR and the vertical coordinate is the TPR, which expresses the proportion of true categories when the predicted categories are positive. The larger the proportion of true categories, the higher the accuracy of the model's predictions. That is, the closer the ROC curve is to the upper left corner, the better the performance. However, for complex tasks, the ROC curves often cross, making it difficult to intuitively judge the advantages and disadvantages. Therefore, in practical tasks, the area under the ROC curve is usually used to judge, i.e., AUC.

3.3.2. Contrasting models

In order to validate the effectiveness of the proposed method and also to reduce the impact of the model implementation details, this chapter selects several classic open source knowledge tracking models as comparison models, namely DKT, DKVMN, and SAKT. For other models that are not open-source or semi-open-source, they are not selected due to the large differences from the original paper in the reproduction process.

The above models are all from the open source code of the original paper of the model, and some of the codes are refactored, but the code logic and hyper-parameter settings are consistent with the original code. For example, the original code of DKT is done in Lua language, and in this chapter, the whole model is refactored with Pytorch framework during the experiment.

3.3.3. Parameter setting

All models in this chapter are implemented using the Pytorch framework, and the hyperparameters of the comparison models are consistent with the open source code. The dropout and the “number of heads” of the multi-head attention of the models proposed in this chapter are set to 0.4 and 8, respectively, and the Adam optimizer is used, with Adam's parameters set to $lr = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = e^{-8}$.

In order to minimize the influence of the data processing method on the experimental results, all models use the data reprocessed in this chapter. The dataset was divided into training set, test set and training set in the ratio of 3:1:1. The test set was used to select the optimal number of iterations. The batch size and embedding dimension were set to 128 for all models.

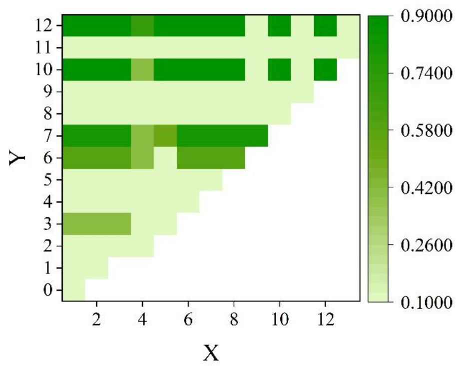
3.3.4. Comparison and Discussion of Results

The results for all datasets on all models are shown in Table 1, with bold text showing the best results on the corresponding datasets. It can be seen that the AUC of this paper's model on the 2 datasets of KDDCup has a large improvement over the other models, while the AKT model has a better performance on the 2 datasets of ASSISTment, with an AUC of 0.8777, 0.8917. In addition, the results are not much different between the two RNN-based models (DKT, DKVMN).

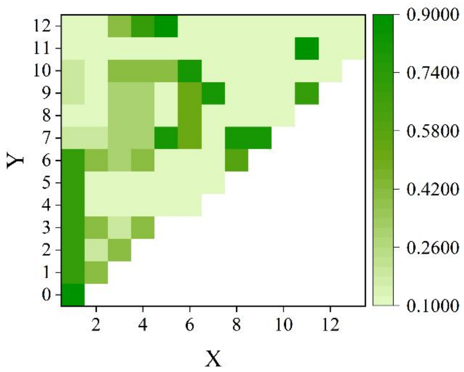
Table 1. All datasets on all models (evaluation metric: AUC).

Dataset	DKT	DKVMN	SAKT	AKT	Model in this article
Assistment2012	0.7237	0.7116	0.6415	0.7754	0.7612
Assistment2017	0.6906	0.681	0.6317	0.7645	0.7307
KDDCup 2010 (a)	0.7607	0.755	0.7257	0.7908	0.8777
KDDCup 2010 (b)	0.8172	0.7868	0.758	0.8334	0.8917

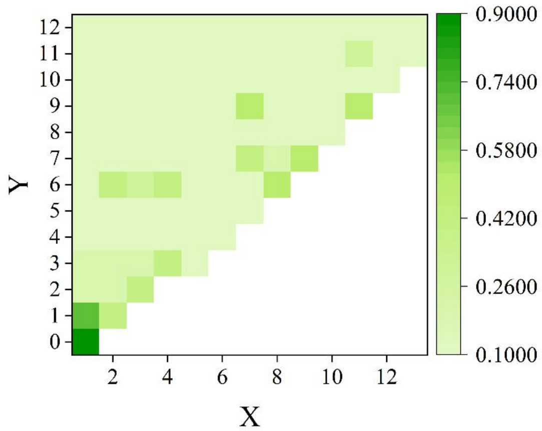
Fig. 2 shows the heat map of the attention values of the proposed model in this paper, which is based on the Assistment2012 dataset, derived from the score values of the second level of attention of the decoder. From left to right are the time interval values, the score matrix without added time interval information and the score matrix with added time interval information. The darker part of the left graph represents a larger time interval, and comparing the corresponding positions of the middle and right graphs, it can be seen that the right graph is significantly lighter in color, indicating a decrease in the attention value. Similarly, it can be found that a decrease in the time interval corresponds to an increase in the attention value. This comparison shows the moderating effect of time interval information on attention values: larger time intervals lead to a decrease in attention values, while smaller time intervals lead to an increase in attention values. This weight modulation is consistent with forgetting behavior in realistic learning and is well interpretable.



(a) 15 minutes



(b) 30 minutes



(c) 45 minutes

Figure 2. Attention visualization.

3.3.5. Visualization of forecast results

In order to visualize the accuracy of the prediction results of this paper's model, this paper selected a student's historical question-answering interaction record data, and used DKT, SAINT+, and this paper's model to predict his/her question-answering performance at the corresponding time step, and the results are shown in Table 2.

The prediction results were filtered and representative exercises 611 and 674 were selected.In the exercise information, 611 and 674 correspond to knowledge points 32, 138, 38, 29 and knowledge points 32, 138, 38, 81, respectively, and according to the annotations given in the dataset, these two exercises have a fairly high degree of similarity.

The model DKT gives a probability prediction of 0.53 for a student being able to answer the first occurrence of Exercise 611 correctly, which rather predicts a result that could be answered incorrectly as well as correctly in the reality of doing the question, and subsequently gives a probability prediction of 0.53 for the occurrence of Exercise 611 again in the sequence. In the real learning behavior, if students continuously answer a certain exercise correctly or incorrectly, it indicates to a certain extent that students have a poor grasp of the knowledge contained in this question. If the model is able to learn and grasp the state of students' knowledge mastery, it should change the predicted probability according to the performance of answering questions. In this sample, DKT performed poorly on the task of tracking students' knowledge mastery status and predicting future performance.

Model SAINT+ gave a probability prediction of 0.37 for a student being able to answer the first occurrence of Exercise 611 correctly, which comes from the fact that model SAINT+ learns better about the correlation between information about the exercise and information about the answer interaction. For the first occurrence of Exercise 611, SAINT+'s prediction favored that students would answer the question incorrectly. To some extent, SAINT+'s unique way of embedding information and the design of the attention mechanism help to improve the model's prediction performance.

The model designed in this paper has good prediction performance on this sample. It is worth noting that when Exercise 674, which is highly similar to Exercise 611, appears for the first time, the model in this paper tends to give a prediction of a possible correct answer with a probability higher than 0.53 based on previous interactions where students have answered Exercise 611 correctly. This is not the same as the prediction given by the model SAINT+. In terms of model design, the model in this paper has multi-hot information embedded in the network for the information on the knowledge points of the exercises, and the model may have learned the correlation information between the exercises and the knowledge points to give more accurate predictions when encountering similar exercises.

Table 2. Visualization of prediction results from different models.

DKT	0.53	0.53	0.53	0.59	0.71	0.75
SAINT+	0.37	0.35	0.47	0.49	0.41	0.85
Model in this article	0.37	0.51	0.63	0.47	0.64	0.80
Question number	611	611	674	674	674	611
Answer status	0	1	0	0	1	1

4. Personalized learning paths based on knowledge graphs and student levels

4.1. Methods for generating learning paths

Learning path generation module is the key module of this recommender system, and its main function is to generate a learning path that meets the learner's characteristics based on the learner's knowledge level and learning style. In the system, according to the user's learning needs, determine the learning objectives, the system from the domain knowledge model to find the target knowledge points, according to the domain model to find out the target knowledge points corresponding to one or more successor knowledge points, to determine the learner's existing level of knowledge, that is, to determine the learner's mastery of the various successor knowledge points, to record the current not-zero successor knowledge points, and so on, until we find the knowledge points which have no knowledge point that does not have a predecessor knowledge point, and so on, until we find a knowledge point that does not have a predecessor knowledge point.

4.2. Adaptive Learning Path Recommendations

4.2.1. Incoming learner personalization characteristics

Learning style determines the type of learning resources suitable for the user. Users are tested for their learning styles after entering the system to initialize their learning styles, and then their learning styles are modified based on rule mining online learning behaviors, which ultimately results in the learner's characteristics in the four dimensions and the formation of learning style parameters with a certain degree of dynamism. In this study, the learner's learning goal is a milestone for the knowledge points within this course, which is the starting point for reasoning, and its successor knowledge points are found according to the goal in order to make the recommendation of learning paths.

4.2.2. Ontological Reasoning Rule Setting

Since the relationship between the terms has been established in the domain ontology library, then the learner's learning objective is passed in, and using this as a starting point to find the predecessor and related knowledge points of the knowledge point, the set of predecessor knowledge points of the learner's learning objective can be obtained by using inference techniques, and then passed into the algorithmic processing module for further optimization and processing, and ultimately generating the learning path.

4.2.3. Learning path recommendation based on ant colony algorithm

In Ant Colony Algorithm [44] three main components are involved: pheromone, heuristic information and probability of selection of learning objects. Heuristic information and pheromone as the important parameters of this algorithm, the magnitude of the value determines the final recommendation result.

(1) Heuristic Information Recognition

Learners with different knowledge levels and learning styles have different preferences for learning objects, so the heuristic information is determined by matching user characteristics and learning object attributes.

In this study, the learner features and learning object attributes are matched from two dimensions, and the Euclidean distance is used for the similarity calculation between the vectors. During the calculation process, the smaller the value obtained as a result, the more similar the two are. Then the similarity calculation formula between the learner's knowledge level and the learning object's difficulty coefficient is as follows:

$$d(kl,dl)=\sqrt{\left(\sum_{i=1}^{n}\left|kl_i-dl_i\right|^2\right)} \tag{7}$$

Similarly, the similarity between the learner's learning style and the learning object's knowledge expression is calculated as follows:

$$d(ls,rf)=\sqrt{\left(\sum_{i=1}^{n}\left|ls_i-rf_i\right|^2\right)} \tag{8}$$

To summarize, the heuristic information in ACO recommendation algorithm can be expressed as:

$$\eta_{ij}(t)=d(kl,dl)*d(ls,rf)=\sqrt{\left(\sum_{i=1}^{n}\left|kl_i-dl_i\right|^2\right)}*\sqrt{\left(\sum_{i=1}^{n}\left|ls_i-rf_i\right|^2\right)} \tag{9}$$

(2) Pheromone Recognition

In the ant colony algorithm, using $m_{ij}(t)$ to denote the intensity of the pheromone, $\Delta m_{ij}^{a}(t)$ to denote the total number of learners, and $\Delta m_{ij}^{s}(t)$ to denote the number of learners of the same kind, the pheromone updating is given by the formula:

$$m_{ij}(t+1)=(1-v)*m_{ij}(t)+\Delta m_{ij}^{a}(t)+\Delta m_{ij}^{s}(t) \tag{10}$$

where v denotes the volatilization rate of the pheromone.

(3) Selection probability

According to the basic principle of ACO algorithm, corresponding to the basis of the inspirational information and pheromone set in this paper, the probability of the learner when choosing the next learning object is:

$$p_{ij}(t)=\frac{\eta_{ij}(t)*m_{ij}(t)}{\sum\eta_{ij}(t)*m_{ij}(t)}$$
$$=\frac{\left[\sqrt{\left(\sum_{i=1}^{n}\left|kl_i-dl_i\right|^2\right)}\sqrt{\left(\sum_{i=1}^{n}\left|ls_i-rf_i\right|^2\right)}\right]*\left[(1-v)m_{ij}(t-1)+\Delta m_{ij}^{a}(t-1)+\Delta m_{ij}^{s}(t-1)\right]}{\sum\left[\sqrt{\left(\sum_{i=1}^{n}\left|kl_i-dl_i\right|^2\right)}\sqrt{\left(\sum_{i=1}^{n}\left|ls_i-rf_i\right|^2\right)}\right]*\left[(1-v)m_{ij}(t-1)+\Delta m_{ij}^{a}(t-1)+\Delta m_{ij}^{s}(t-1)\right]} \quad (11)$$

(4) Learning path recommendation algorithm description

The steps of the ant colony recommendation algorithm based on the user profile of sports professional learners are as follows:

Step1: Construct all possible learning paths from the Chinese learning domain library of sports majors according to the current user's learning objectives.

Step2: Initialize each parameter, which includes the matching degree of the learner's cognitive level with the difficulty of the learning object (kl, dl), the matching degree of the learner's style with the type of the learning object $d(ls, rf)$ the degree of volatility of the veggie v.

Step3: Obtain the cognitive level and learning style of the current learner r.

Step4: Determine the neighboring users of the current learner based on the cognitive level and learning style among the learners who have accomplished the same learning objectives.

Step5: Obtain the learning path of each neighboring user based on the learning behavior records in the system.

Step6: Update the pheromone based on the evaluation of neighboring users.

Step7: Calculate the selection probability of all possible next learning objects for the current learner based on the learning objects he/she has completed.

Step8: Arrange all possible path selection probabilities in descending order and select the path with the highest probability to recommend to the current learner.

4.3. Learning path recommendation experiment

4.3.1. Overview of the experiment

(1) Experimental Environment

In this paper, we implement a personalized learning path recommendation module that supports schema knowledge on this teaching prototype system. After logging into the system, the user can view the domain knowledge building diagram, view or modify the user's personal information, or learn domain knowledge. When learning domain knowledge, the system starts the personalized learning path recommendation module supporting schema knowledge to provide users with recommended paths.

(2) Experimental Design

This experiment obtains and simulates the learning characteristics and learning paths of past users by means of a questionnaire. Recommended learning paths are given to all experimental subjects, and experimental subjects are arranged to learn the target knowledge areas. The experimental objects are divided into two groups, and after the experiment is finished, the feedback information of the experimental objects is obtained, and the effectiveness, accuracy and adaptability of the learning path recommendation algorithm proposed in this paper to support pattern knowledge are analyzed in combination with the experimental results.

(3) Experimental process

The experiment obtains the learning characteristics of the users through the learning characteristics questionnaire. The subjects of the experiment are 30 college students majoring in physical education. In the experiment, only one dimension of “perception type characteristics” is extracted from the behavioral characteristics of the students, and the questionnaire content also involves only this dimension. The experimental subjects were evenly divided into two groups, each group of 15 people. The first group learns according to the path recommended by the algorithm, and the second group learns according to the default path.

4.3.2. Learning path simulation

The learner is set up with a total of 15 mobile learning resources, each of which contains a random number of skill points, and the learner's characteristic data and the attribute parameters of the learning resources are simulated by the stochastic function of MATLAB. The ant colony algorithm is used to recommend mobile learning resources for learners and generate learning paths, as shown in Fig. 3. In the figure, the execution result under the ACO algorithm will output multiple local optimal values, which means that for the learner, the learning resources corresponding to these multiple positions are recommended to the learner, and at the same time, the magnitude of the objective function values corresponding to these multiple positions determines the order in which the learner learns these learning resources, i.e., the learning path. In the figure, the objective function values of the three locally optimal positions are 1.986227, 3.971639, and 5.183436, respectively.

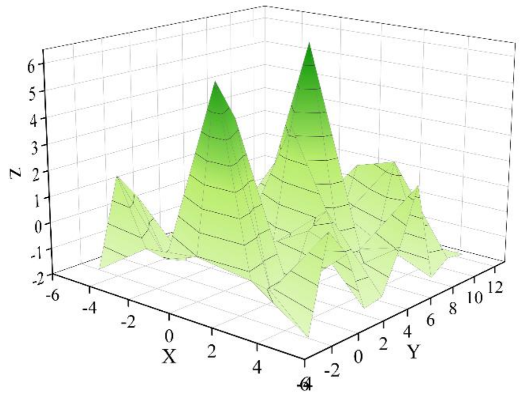


Figure 3. 3D graph of the objective function execution result.

The correspondence between the local optimal location learning resource number and the objective function value is shown in Table 3. From the table, it can be clearly seen that the objective function value of resource No. 12 is the largest, so it should be learned first, while the objective function value of learning resource No. 1 is the smallest, and it should be learned last. From the simulation results of the algorithm, it can be seen that for a total of 15 learning resources contained in the learner's learning objectives, the three learning resources 6, 8, and 12 are recommended to the learner, and the corresponding learning path for the learner is 12→6→8.

Table 3. Resource ID and objective function value correspondence.

Resource ID	6	8	12
Objective function value	1.986227	3.971639	5.183436

4.3.3. Analysis of experimental results

(1) Algorithm effectiveness analysis

The effectiveness of the algorithm examines whether the recommended path can effectively improve students' learning performance and shorten their learning time. It is known from the experimental process that 30 experimental subjects were divided into two groups to learn the knowledge field of "Introduction to Physical Education", 15 people in each group. The subjects in the first group studied according to the path recommended by the algorithm, and the subjects in the second group studied according to the default path. The learning time and average test scores of the two groups are shown in Table 4.

As can be seen from the table, the average learning time of the experimental subjects in the first group is 375.67 minutes, and the average learning time of the experimental subjects in the second group is 395.47 minutes; the average test score of the experimental subjects in the first group is 85.09 points, and the average test score of the experimental subjects in the second group is 82.81 points.

Table 4. Comparison of learning duration and average test scores of experimental subjects.

First group			Second heat		
Subject ID	Study time (minutes)	Test average score	Subject ID	Study time (minutes)	Test average score
1	392	78.3	1	402	79.1
2	386	87	2	386	84.2
3	370	90.1	3	373	87
4	362	83	4	392	80
5	402	87.2	5	412	90.8
6	360	87.9	6	423	84.9

7	363	81.2	7	389	83.7
8	356	84.6	8	363	80.8
9	353	85.2	9	416	76.9
10	391	85.3	10	370	82.2
11	383	79.8	11	382	79.4
12	386	87.7	12	399	83
13	395	81.4	13	393	76
14	364	85.6	14	432	88
15	372	92	15	400	86.2
Average value	375.67	85.09	Average value	395.47	82.81

The data in Table 4 were transformed into the figures shown in Figures 4 and 5. From the figure, it can be visualized that the experimental subjects in the first group spent more time learning overall than the experimental subjects in the second group, and the average test scores of the experimental subjects in the first group were overall greater than those of the experimental subjects in the second group. From the results, it can be seen that the average score of the experimental subjects who learn according to the recommended path is better than that of the subjects who learn according to the default path, and the time spent on learning is also shorter. It can be seen that the algorithm proposed in this paper has good effectiveness.

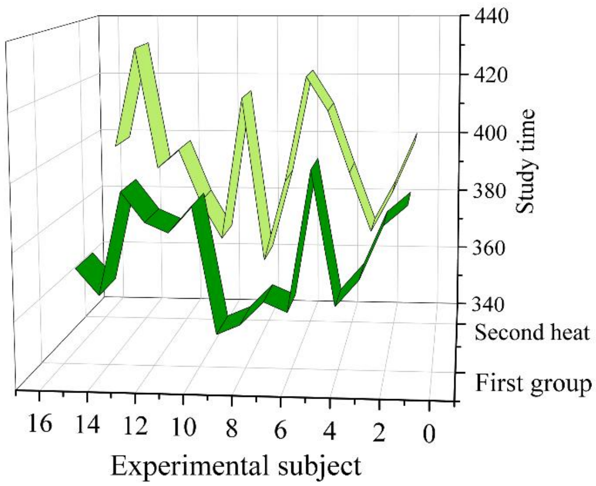


Figure 4. Experiment object learning duration comparison.

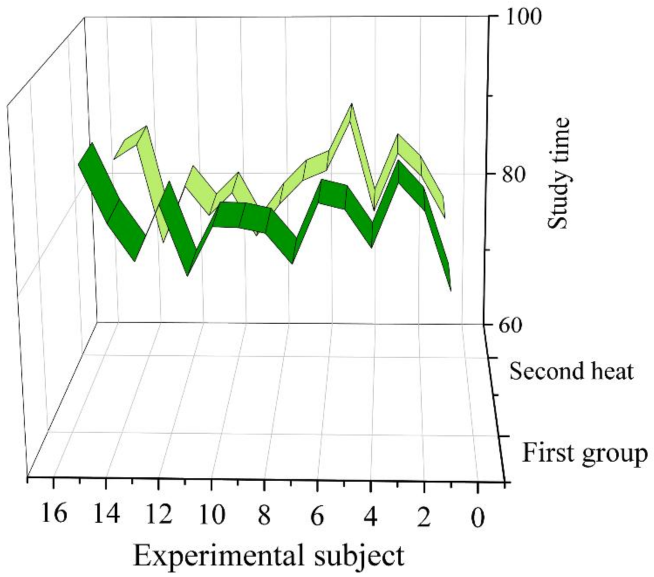


Figure 5. Comparison of average test scores for experimental subjects.

(2) Algorithm accuracy analysis

Algorithm accuracy analysis mainly examines whether the learning path given by the recommendation algorithm matches the user's needs. This experiment analyzes the accuracy of the algorithm from two perspectives: recommendation matching degree and F1 value.

1) Recommendation matching degree

Recommended Match Degree (RMD) refers to the ratio of the number of duplicate segments between the learning path recommended to the user and the user's favorite learning path to the number of all segments in the path. For example, a user favorite learning path for $P_1 = \{a, b, c, d, e\}$, the algorithm is recommended to the user's learning path for $P_2 = \{a, b, c, f, g\}$, the same section number 3, Then the recommendation matching degree of this user is 0.6. The recommended matching degree of the experimental subjects is shown in Table 5. The minimum value of the recommended matching degree of the experimental objects is 0.4794, the maximum value is 0.9004, and most of the values are between 0.68 and 0.90, which indicates that there is a high degree of similarity between the learning paths recommended by the algorithm in this paper and the students' favorite learning paths. Therefore, the learning path recommendation algorithm proposed in this paper has good accuracy.

Table 5. Recommended match for experiment participants.

Subject ID	RMD	Subject ID	RMD	Subject ID	RMD
1	0.8478	11	0.8478	21	0.6899
2	0.7952	12	0.6373	22	0.7952
3	0.7425	13	0.6899	23	0.9004
4	0.532	14	0.8478	24	0.7425
5	0.6899	15	0.7952	25	0.7952
6	0.7952	16	0.8478	26	0.8478
7	0.4794	17	0.7952	27	0.5846
8	0.9004	18	0.5846	28	0.6899
9	0.6373	19	0.7952	29	0.7952
10	0.7425	20	0.8478	30	0.7952

2) F1 value

Precision refers to the proportion of all correctly retrieved items to all items that were actually retrieved. Recall refers to the proportion of all correctly retrieved items to all items that should have been retrieved. The formula for calculating the precision rate is:

$$P = \frac{N_{rl}}{N_r} \tag{12}$$

Recall is calculated by the formula:

$$R = \frac{N_{rl}}{N_{rl} + N_{ul}} \tag{13}$$

The F1 value is the reconciled mean of precision and recall, and the F1 value is calculated by the formula:

$$F_1 = \frac{2PR}{P+R} \tag{14}$$

The larger the F1 value, the better the performance of the algorithm.

Recommended learning path evaluation questionnaire, the user's rating is a 5-point scale, in this paper, 1 to 2 points indicate that the user does not like, 3 to 5 points indicate that the user likes, according to the questionnaire obtained by the experimental subjects on the recommended path in the three dimensions of the evaluation of the statistical information is shown in Table 6:

Table 6. Evaluation information of the experiment object on the recommended path.

Evaluative dimension	Statistics of evaluations by level						
	1	2	3	4	5		
This learning path meets my needs	0	1	1	7	25	1	28
I accept the difference between the recommended path and the selected path	0	2	2	20	10	2	27
I think the recommended path is more suitable for my needs	0	3	8	18	7	3	26

According to Table 6, the precision and recall data are obtained as shown in Table 7. 1, 2 and 3 in the table represent the three dimensions of evaluating the recommended path, respectively. The F1 values of the three evaluation dimensions of the recommended path are all above 0.6, indicating that the research subjects are more satisfied with the path recommended by the algorithm, which further proves that the learning path recommendation algorithm proposed in this paper has good precision.

Table 7. Precision and recall data table.

	Number of recommended learning paths			Number of unrecommended learning paths		
This learning path meets my needs	1	2	3	1	2	3
I accept the difference between the recommended path and the selected path	28	27	26	30	30	30
I think the recommended path is more suitable for my needs	1	2	3	0	0	0
This learning path meets my needs	30	30	30	30	30	30
F1 value	0.657	0.639	0.658	0.612	0.602	0.631

(3) Algorithm adaptation analysis

The knowledge domain of this experiment contains a total of 19 knowledge points, and this paper utilizes the mean value of the degree of matching between the 19 learning objects in the recommended learning path and the learning characteristics of the experimental subjects, i.e., the degree of adaptation, to measure the adaptability of the algorithm. Therefore, the formula for the algorithm adaptation degree can be obtained as follows:

$$S = \frac{\sum_{j=1}^{19} Match\left(s_o, k_j\right)}{19} \tag{15}$$

The value interval of S value is $[0, \sqrt{2}]$. From the formula of Euclidean distance, it can be seen that the smaller the value of S, the more the characteristics of the learning object on the learning path match the learning characteristics of the user, that is to say, the better the adaptability of the learning path recommended by the algorithm. The experimental results are shown in Table 8.

Table 8. Recommended path fitness results.

Subject ID	S value	Subject ID	S value	Subject ID	S value
1	0.1452	11	0.1983	21	0.2074
2	0.1911	12	0.2813	22	0.2262
3	0.2193	13	0.1331	23	0.1783
4	0.1098	14	0.0955	24	0.3085
5	0.2236	15	0.1611	25	0.3176
6	0.1486	16	0.1219	26	0.2138
7	0.3094	17	0.2221	27	0.0920
8	0.1643	18	0.3136	28	0.1777
9	0.1992	19	0.2029	29	0.2040
10	0.1199	20	0.1215	30	0.1861

The data in Table 8 is transformed into Figure 6 from the figure, it can be intuitively seen that the adaptations of the recommended paths are all below 0.35, and most of them are between 0.1 and 0.21. It can be seen that the learning objects on the recommended learning paths are more in line with the user's learning characteristics, so the learning paths recommended to the user by the algorithm proposed in this paper have a high degree of adaptability.

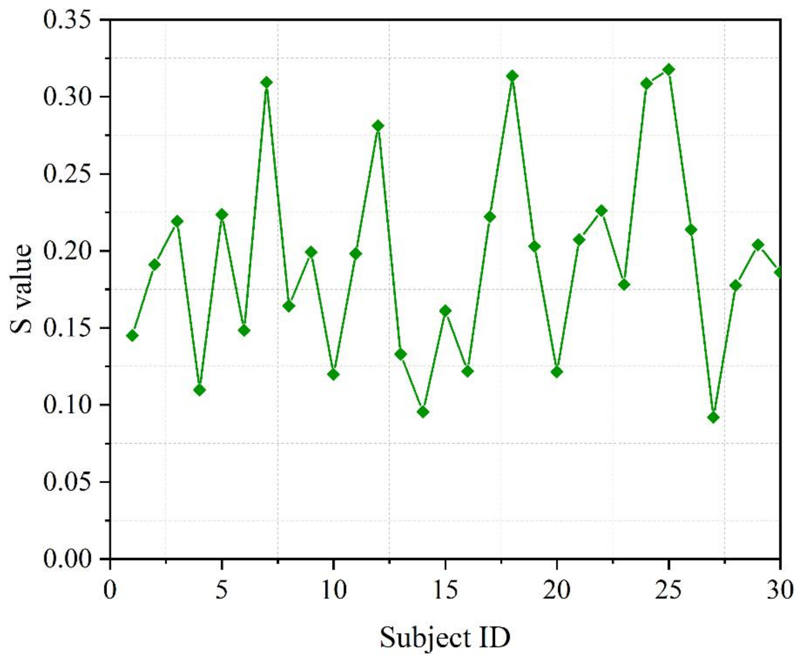


Figure 6. Recommended path fitness results.

5. Conclusion

In this paper, a new knowledge tracking model based on the Transformer structure is proposed by constructing a knowledge map of sports professional courses that incorporates the elements of Civics and Politics, and comparing it with four classical models on four public datasets on this basis. Then a personalized learning path is generated based on the Ant Colony algorithm, and the corresponding learning resources are personalized recommended. Finally, 30 college students majoring in physical education were used as experimental subjects for experimental validation. The research conclusions are as follows:

(1) The results of the comparison experiments show that the AUC of the knowledge tracking mode-text model proposed in this paper is 0.8777 and 0.8917 on the two datasets of KDDCup, which side by side demonstrates its powerful feature extraction ability on the knowledge tracking task. Secondly the prediction visualization verifies that the model's architecture and mechanism design has an enhancing effect on the model's fitting ability and prediction performance.

(2) Simulation experiments are carried out under matlab platform and feasibility and effectiveness experiments are designed to verify that the personalized learning path based on ant colony algorithm in mobile learning environment can provide better learning navigation support services.

(3) The adaptability of the recommended paths of the personalized learning path recommendation algorithm proposed in this paper are all below 0.35, with good effectiveness, accuracy and adaptability.

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