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Article

Research on the Teaching and Interaction Mode of Collaborative Development of Party Building and Civic and Political Education in Colleges and Universities Based on Artificial Intelligence

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Abstract: Both ideological and political theory courses and student party building are the main channels of ideological and political education for students in colleges and universities in the new era, and they are important handles for cultivating builders and successors of socialism with Chinese characteristics. For this reason, after exploring the teaching strategy of AI-enabled synergistic development of party building and ideological and political education in colleges and universities, the article designs a Q&A interactive system based on the knowledge level of students' party building and ideological and political education. The system first improves the Bayesian knowledge tracking model and introduces the correlation degree between the knowledge points to realize the tracking of the knowledge level of students' Party building and Civic and political education, and on this basis, it combines the bi-directional threshold recurrent unit neural network and the attention mechanism to design a Q&A model based on the threshold recurrent unit. The article finally tests the teaching interaction effect of the model and finds that the highest adjusted residual value is writing-reading with a residual value of 0.663, which is mainly due to the small number of behaviors, which does not constitute significance. Therefore, the method of this paper can help to improve the interactive effect of Civics classroom teaching integrating party building knowledge.

Keywords: BiGRU; Attention Mechanism; Bayesian Knowledge Tracking Model; Question and Answer System Model; Party Building and Civic Education

1. Introduction

The university stage is a major turning point for adolescents, who will change from passive learning in primary and secondary schools to independent learning in universities, and the campus environment will change from simple to complex, and gradually realize the transition from the campus to the society [1-3]. At the same time, the university is a "small society" with both opportunities and challenges, and college students can come into contact with all kinds of inputs, things and objects, as well as a variety of resources and platforms provided by the school [4], but students at the university level are still in the stage of immaturity of thought, easy to feel lost and confused, and subject to the influence of the outside world and misguided, in order to give full play to the role of ideological and political education in students' ideological development. It is necessary to give full play to the guiding function of ideological and political education in students' thinking, guide them to develop good moral qualities and become a person beneficial to the harmonious development of society [5].

Colleges and universities are the main position for realizing the fundamental task of "establishing morality and educating people" [6], and they must give full play to the function of nurturing people and hearts while assuming the responsibilities of preaching, teaching and solving puzzles, so as to cultivate socialist builders and successors for the country [7]. Party building work is the core of ideological and political education, while ideological and political education is an important way of party building, both of them have certain overlap in the main body of nurturing, nurturing content, nurturing goals, but the reality of the work process still exists a certain degree of difference [8-9]. Student party building work and ideological and political education work, the two are complementary, mutual promotion, complementary relationship [10], in order to cope with the complex social environment and international situation that colleges and universities are currently facing, we must always adhere to the guidance of the scientific theory of Marxism, firmly grasp the leadership of the party in the ideological work of colleges and universities, and strengthen the construction of grass-roots party organizations at the same time, strengthen the ideological and political education work In order to promote the integration and synergistic development of the two, and to jointly contribute to the education and cultivation of young people with “ideals, morals, culture and discipline” [11-13].

With the help of advanced technology in the field of artificial intelligence, it has become a key entry point to enhance the effect of the integration of party building and ideological and political education in colleges and universities by promoting the in-depth integration and innovative use of resources [14]. Artificial intelligence refers to the technology that enables computer systems to simulate, extend and enhance human intelligence, including the ability to perceive, learn, reason, make decisions and solve problems [15-17]. It aims to create intelligent systems that can perform tasks autonomously, adapt to new situations and learn from experience. The composition of artificial intelligence technology includes multiple subfields and technologies, and one of the core components is machine learning, which enables machines to learn and make predictions or decisions based on data [18]. In the intelligent transformation of ideological and political education for college students in colleges and universities, the use of AI technology to integrate and analyze the data of students' learning behavior, performance records, interests and hobbies can provide them with personalized learning suggestions and resources [19-21]. In terms of party building in colleges and universities, artificial intelligence interacts with users with unique information, and this special form of interaction naturally provides new ideas for party building in colleges and universities.

The article first explores the strategy of collaborative nurturing mechanism between the teaching of Civic and Political Theory Classes and students' party building work, based on which a Bayesian knowledge tracking model based on multiple interactions is proposed. By adding the correlation of knowledge points and enhancing the interaction and updating methods on the basis of the original Bayesian knowledge tracking model, the model is tested on a public dataset. Further, by introducing the bidirectional threshold recurrent unit (BiGRU) neural network and attention mechanism, a question and answer system model based on the combination of bidirectional GRU and attention mechanism is designed, and performance comparison experiments are carried out between the question and answer system model and other models, and its intelligence is tested, and aspects such as changes in the behavior of the teacher and student and the real-time engagement in the student's behavior are analyzed under the use of the model.

2. AI-enabled synergistic development mechanism for party building and civic education in colleges and universities

Synergistic nurturing working mechanism is the foundation and guarantee for the synergistic nurturing work of ideological and political theory course teaching and student party building work, only by establishing or perfecting the synergistic working mechanism can we effectively promote the synergistic nurturing of ideological and political theory course teaching and student party building work.

1) Strengthen the top-level design, establish collaborative parenting work mechanism

Colleges and universities should further improve their understanding, strengthen the top-level design, and take the teaching of ideological and political theory courses and student party building to coordinate and educate people as an important hand of the school to implement the fundamental task of establishing morality and educating people. Adhere to the unified leadership of the party committee of the school, the ideological and political theory course teaching and student party building coordinated nurturing work as the “secretary project” to grasp, the relevant functional departments and the secondary colleges and universities in all aspects of the joint management, to promote the work on the ground. Establishment of school and secondary colleges, functional departments and secondary colleges and secondary colleges between the coordination of nurturing work mechanism, the teaching of ideological and political theory courses and student party building work with the same planning, the same promotion, the formation of a department led by a number of departments to promote the collaborative nurturing pattern, the realization of the teaching of ideological and political theory courses and the work of the student party building in the same direction, the goal of synergistic nurturing. The School of Marxism coordinates the establishment of collaborative education projects, process monitoring, effectiveness evaluation or project acceptance and results promotion. The organization and personnel department of the school party committee builds a platform for exchange and communication between teachers of ideological and political theory courses and student party building workers, establishes the school's teacher pool, incorporates teachers of ideological and political theory courses into the members of the teacher pool, carries out thematic seminars or workshop activities on a regular basis, and organizes learning and exchange activities for teachers of ideological and political theory courses and student party workers.

2) Strengthening team building and constructing “1+N” collaborative parenting model

The key to collaborative nurturing between the teaching of ideological and political theory courses and student party building in colleges and universities is to stimulate the enthusiasm of teachers of ideological and political theory courses and student party workers to build and nurture people together. Colleges and universities should pay attention to team building, integration of on-campus faculty resources, the establishment of a ideological and political firm, industry to establish a “dual tutor” system, for each student party activists equipped with an ideological and political theory course teachers and practice instructors, to guide the healthy growth of party activists. The school party committee and party school should fully mobilize the ideological and political theory teachers to actively participate in the education and training of the student party activists, development objects and preparatory party members, and invite the teachers of ideological and political theory to participate in the revision of the education and training plan and training content of the party school, so as to improve the training plan and training content.

3) Establish a learning and exchange system to improve the awareness and ability of collaborative parenting

Schools can establish a learning and exchange system, such as a fixed time every month as a learning and exchange day for teachers of ideological and political theory courses and student party workers, organizing teachers of ideological and political theory courses and student party workers to exchange and share, or in the form of workshops, organizing teachers of ideological and political theory courses and student party workers to share and exchange their learning. Meanwhile, experts from outside the university can also be invited to the university to carry out lectures or experience sharing on relevant topics. In addition, through learning and exchange, it can promote the coordinated development of teachers of ideological and political theory courses and student party workers, integrate the existing faculty strength, and continuously improve the effect of collaborative education.

4) Construct “ideological and political theory course +” education and teaching mode, forming a natural linkage between the teaching of ideological and political theory course and the teaching of party courses.

Ideological and political theory course teaching and student party building work synergistic nurturing, but also reflected in the synergy of education and teaching content. The author believes that the “ideological and political theory course +” education and teaching model can be constructed, in the teaching of ideological and political theory course, the basic theoretical knowledge of the party is included in the teaching content, and the theoretical knowledge of the party is taught to the students at the right time. Legal foundation, situation and policy and other ideological and political theory course content. Through the integration of the two, students are given political theory education, education on Party rules and regulations, education on the purpose of the Party, education on revolutionary traditions, education on situation and policies, and education on knowledge and skills, etc., so as to guide students to strengthen their political training, stimulate their political enthusiasm, cultivate their love for the Party and patriotism, and strive to solve the problem of the ideology of students' activists in joining the Party.

5) Improve the relevant system to ensure the effective implementation of collaborative parenting

In order to ensure the effective implementation of collaborative education, schools should establish relevant systems, strengthen the incentive mechanism, improve the teaching reform and scientific research system, and utilize the performance leverage to solidly promote the “three full education”. Establish an evaluation system for the effectiveness of the teaching of ideological and political theory courses and student party building work, regularly evaluate the teaching of ideological and political theory courses and student party building work, and form a dynamic, normalized, rolling evaluation mode. The effectiveness of the teaching of ideological and political theory courses and the collaborative education of students' Party building work is taken as an important content of the performance appraisal of the relevant functional departments and secondary colleges, as well as the appraisal of the Party building work of the students' Party branches. Increase the strength of scientific research awards, in the work of Party school scientific research commendation and reward, should emphasize the requirements of the ideological and political theory course teaching and student party building work collaborative nurturing, increase the support for the excellent results of the ideological and political theory course teaching and student party building work collaborative nurturing.

3. Research and realization of the knowledge tracking model of ideology and politics integrating party building

3.1. Knowledge point tracking model design

Accurate tracking of students' Civic and Political knowledge for integrating party building is the basis for the system to realize intelligent recommendation.The BKT model is one of the most commonly used Civic and Political knowledge point tracking models for integrating party building, but it does not take into account the impact of knowledge point association on learning, and the model can only be updated by test results. Considering the shortcomings of the BKT model in this aspect, this paper designs an improved multi-interaction Bayesian model (IBKT) to track students' learning status, and the framework of the IBKT model is shown in Figure 1. Compared with the original BKT model, IBKT covers more elements and processes. The elements in it contain basic information such as the student's number, name and age, as well as the student's personality indicators and mastery of each Civic and Political knowledge point integrating party building, such as affinity for people, responsibility and study habits [22]. The process of which contains both the learning process and the observation process. The learning process refers to the process in which the degree of mastery of knowledge points changes subsequently after a period of learning. The observation process contains two kinds of classroom observation and test observation. Classroom observation is the self-perceived mastery of knowledge given by students through classroom polling, and test observation is the learning situation shown by students through test results. Since the student learning process is usually intangible, such model updating can correct errors arising from the evolution of one's mastery of knowledge points during the learning process.

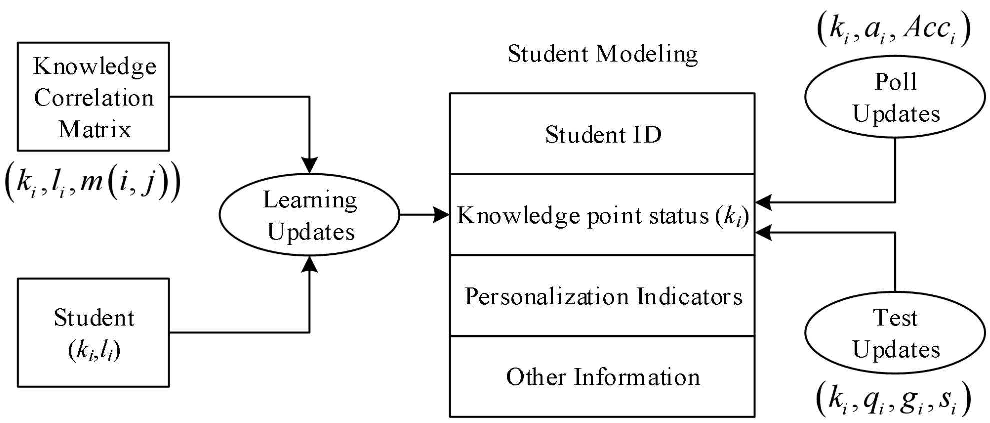

Figure 1. IBKT model framework.

The IBKT model, supported by more elements and processes, can achieve far more than the BKT model can give to the teaching and learning process. In terms of knowledge tracking, the IBKT model can update and track students' learning status in a more timely manner through a variety of interactive processes. At the same time, these interactions will not be so frequent or abrupt as to affect students' original learning status and habits. In addition to knowledge tracking, students' personality indicators and learning profiles allow teachers to have a more comprehensive understanding of their students and make better decisions on activities that require consideration of students' personalities, such as grouping activities.

IBKT first defines the state space $k_i \in K$ of a student's mastery of a knowledge point, where k_i denotes the mastery of the student's i th KP at the current moment. In this context, $k_i = 0$ means that the student has no knowledge of the KP at all, while $k_i = 1$ means that the student has full mastery of the KP. Subsequently, the model defines the student's ability to learn the knowledge point as $l_i \in L$, with l_i denoting the student's ability to learn the i th knowledge point.

In systematic learning, knowledge points are often interconnected with each other, but the BKT model ignores such correlations and does not take such connections into account in the model, which is one of its shortcomings. Due to such correlation, when learning some knowledge points, students usually need to learn some other related knowledge points as prior knowledge first. Therefore, the IBKT model introduces a knowledge point correlation matrix $m(i,j) \in M$, where $m(i,j)$ denotes the degree of dependence of the i th knowledge point on the j th knowledge point, and when $m(i,j)$ is 0, it means that there is no linkage between the two knowledge points at all, when $m(i,j)$ is 1 it means that the learning of i th knowledge point is a necessary prerequisite for learning of j th knowledge point, which has the advantage of being a prerequisite for learning some other related knowledge points. which has the strongest dependency on the necessary antecedents.

The model sets an initial learning ability l_i that indicates the efficiency of learning the i th knowledge point without being influenced by any antecedent knowledge point, i.e., for any j -value that is 0 or for the knowledge point j that has been fully mastered. This initial learning ability depends only on factors such as one's intellectual condition and study habits. And after considering the correlation of knowledge points, the model uses $\tilde{l}_i$ to represent the real learning efficiency of the i th knowledge point, and the formula is shown in equation (1):

$$\tilde{l}_i = l_i \prod_{j=1}^{i-1} \left[1 - m(i,j) \cdot (1 - k_j)\right] \tag{1}$$

In the formula, the model only calculates the effect of the first knowledge point to the $i-1$ th knowledge point on the knowledge point i, which is due to the fact that the order of knowledge points in the system corresponds to the learning order of knowledge points in the course lesson plan, and thus the subsequent knowledge points will not be used as the antecedent knowledge points of the i th knowledge point.

Based on this design, the model associates the learning of the Civic and Political Knowledge Points of Integrated Party Building with the learning status of the antecedent knowledge points. Its defined knowledge point association matrix M is shared by all students in the course and can be defined by the instructor with senior teaching experience in the course.

From the above, the model describes the students' learning process as equation (2):

$$k_i^{t+1} = k_i^t + (1 - k_i^t)\tilde{l}_i \cdot h \tag{2}$$

where t denotes that it is currently at moment t. k_i^t denotes the mastery degree of the student for the i th knowledge point at t moment. h denotes the credit hour occupied by the learning time of the knowledge point from the last learning to the present, and usually a credit hour is set to be 15 minutes.

In an exam or test, when the student participates in the quiz of the question q_i related to the i th knowledge point, $C(q_i)$ is the probability of answering the question q_i correctly, while $W(q_i)$ is the probability of answering the question q_i incorrectly. The model defines the student's test parameters $(g_i, s_i) \in T$, where g_i is the probability of answering question q_i correctly without mastering the i th point, i.e., guessing correctly in the colloquial sense. And s_i is the probability of not answering question q_i correctly without having mastered the i th knowledge point, i.e., a miss in the popular sense. Based on this, the two formulas underlying the model observation process are shown in equations (3) and (4):

$$C(q_i) = k_i^t(1 - s_i) + (1 - k_i^t)g_i \tag{3}$$

$$W(q_i) = 1 - C(q_i) \tag{4}$$

In addition, $Score(q_i)$ represents the score of question q_i and $grade$ denotes the total score of a test, which is calculated as shown in equation (5):

$$grade = \sum_{i=1}^{num} C(q_i) score(q_i) \tag{5}$$

where num refers to the number of questions in the test. Each question in the test is associated with a corresponding knowledge point, and if a question involves n knowledge points, a linear combination of coefficients of $\sum_1^n \alpha_i = 1$ is used to quantify the amount of influence that multiple knowledge points have on it, where α_i is the weight that the i th knowledge point holds in the question among all the related knowledge points. In this way, a knowledge point-based test can measure a student's mastery of course knowledge points at a given moment.

3.2. Knowledge point tracking process realization

When completing the students' Civic and Political knowledge tracking task of integrating party building, the knowledge tracking process is shown in Figure 2, which is mainly divided into four steps: initialization, learning tracking, classroom tracking and exam tracking [23].

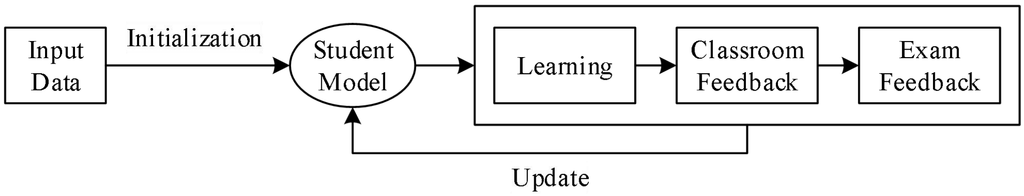

Figure 2. Knowledge point tracking process.

Before the class begins, the parameters of the student model are first initialized based on the student's basic information, previous academic performance or a simple preclass test. Usually, $k_i \in K$ are initialized to 0. Assuming that the students have not studied the relevant content beforehand, l_i is evaluated according to the students' previous grades, (g_i, s_i) are initialized to 0, and Acc_i is initialized to 1.

The second step is the knowledge point tracking based on students' learning behavior. The students' learning history is input into the model, and the model is updated with the knowledge point mastery based on Eq. (2). It is worth mentioning that such an update is an indeterminate update, which is just the model's prediction of the student's current state based on the existing data, and the model does not delete the data before the update.

The third step is the student's classroom tracking, and there are two types of classroom tracking: self-assessment tracking and test tracking.

Self-assessment tracking means that after learning a certain knowledge point, students self-assess their mastery of the knowledge point based on their learning situation. In self-assessment tracking, the model updates K and L based on students' feedback, as shown in equation (6):

$$k_i^{t+1} = \frac{\left[k_i^t + (1-k_i^t)\tilde{l}_i + \widehat{k_i^t} \middle/ Acc_i \right]}{2} \tag{6}$$

Where $\widehat{k_i^t}$ denotes the self-assessed mastery of the student for knowledge point i at moment t. The model chooses the mean of the students' self-assessment results and the prediction results of Eq. (2) as the mastery of the knowledge point at moment $t+1$.

After updating the students' mastery of knowledge points, the model updates the students' learning ability by the inverse operation of Eqs. (1) and (2) as shown in Eq. (7):

$$l_i = \frac{(k_i^{t+1} - k_i^t)}{h \cdot (1-k_i^t) \cdot \prod_{j=1}^{i-1} \left[1 - m(i,j) \bullet (1-k_j) \right]} \tag{7}$$

It is worth noting that self-assessment updates are likewise uncertain updates, where the model does not remove the results of previous accurate updates, usually those made during video quizzes or exams.

Test tracking refers to accompanying quizzes or assignments initiated by the instructor in the classroom, usually questions related to a particular knowledge point, etc. The model obtains the students' accurate mastery of each knowledge point through their correct response rate, and based on this information, K, L, Acc_i and T in the model are updated in the same way as the test tracking, with the difference in the scope of the knowledge points involved.

The fourth step, exam tracking, is the most accurate update in the model and, like test tracking in the classroom, updates most of the parameters in the model. Before obtaining students' grades, the model requires students to give self-assessment grades, based on the ratio of self-assessment grades to actual grades to update the students' self-assessment accuracy as shown in Equation (8):

$$Acc_i = \frac{\widehat{k_i}}{k_i} \tag{8}$$

After the students' results are given, the students calculate the proportion of questions they guessed correctly or made mistakes during the exam according to their actual situation, and the model updates (g_i, s_i) based on this proportion.

The other parameters of the student model are subsequently updated based on the specific exam results, and the model uses the maximum likelihood method to update the student's knowledge point mastery k_i. The objective function $p\left(O \middle| K, L, T\left(g, s\right)\right)$ represents the probability of obtaining the current exam result O under different model parameters $\left(K, L, T\left(g, s\right)\right)$. The corresponding student knowledge point mastery $\tilde{K}$ is obtained by maximizing the value of the objective function as shown in equation (9):

$$p\left(O \middle| K, L, T\left(g, s\right)\right) = \prod_{i=1}^{m} C(q_i) \prod_{j=1}^{n} W(q_j) \tag{9}$$

where m is the number of questions answered correctly. q_i is the number of questions answered correctly. n is the number of questions answered incorrectly. q_j refers to the questions answered incorrectly. Define $\tilde{K}$ that maximizes the value of p as the student's true knowledge point mastery, and the model records the updated value of successive $\tilde{K}$.

Finally, to update the learning ability of students in the model, the model substitutes the two updated true masteries $\tilde{K}$ from two neighboring exams to replace the original knowledge point mastery in Equation (7) for calculation, and obtains the latest and accurate learning ability of students.

3.3. Model Performance Testing

3.3.1. Data set preparation

In this section, the performance of the Civic and Political Knowledge Points Tracking model for Student Integration Party Building will be tested. The test of the model is mainly for its generalization ability. Generalization ability is the prediction ability shown on unknown data, and its quantitative indexes mainly include accuracy rate, precision rate, recall rate, subject characteristics (ROC) curve and area under the ROC curve (AUC), and confusion matrix F1 value.

In this paper, the algorithm mainly applies the information of answer results, number of hints, answer time, knowledge points, etc., so the dataset needs to contain these entries. In addition, the dataset should also satisfy the principle of reasonable distribution of test and training data levels and the principle of independent data distribution, i.e., the training set and the test set should not cross and be in the same distribution state. Because the system is an online platform, learners can not only get the recommendation service, but also the learning process will be recorded, and these data will be filtered and processed to generate new experimental data. In this paper, we use the industry open dataset skill-builder-dat provided by Assistment and the data mining competition dataset ADM-2024 provided by Assistment in 2024, and the main learning process description fields in the dataset are shown in Table 1.

Table 1. Learning process description field.

Field name	Description	Model
Knowledge point ID	Knowledge point D related to the question	√
Answer result	Knowledge point D related to the question	√
Final hint	Did the learner use all the prompts	×
Prompt quantity	The number of prompts used in the current answering process	√
Action Record	All the actions of the learner during the answering process	×

Number of answers	The number of times the current learner answers the current question	×
Consume time	The time consumed in answering questions	√

3.3.2. Model performance testing

The IBKT model applied in this paper integrates the data of the Civics learning process into the knowledge status assessment, in order to improve the accuracy of the knowledge tracking model. In addition, in order to solve the problems of input information reconstruction and fluctuation of prediction results, the model introduces regular coefficients. In the process of testing the model, the strategy of 80% training set and 20% testing set is used. In order to ensure the control variables, the model parameters such as batch_size, hidden_size, etc. are kept the same in the testing process of each dataset.

The model AUC performance is shown in Table 2. In the skill-builder-data dataset, the AUC of BKT and IBKT reaches 0.65478 and 0.91653, and the AUC of IBKT-MF reaches 0.93577 and 0.94058 in both No-Encoder (using encoder) and Use-Encoder (not using encoder). In the dataset ADM-2024, the AUCs of BKT and IBKT were 0.68846, 0.74618, and IBKT-MF-No-Encoder and IBKT-MF-Use-Encoder reached 0.83984, 0.86361.

Table 2. Model AUC performance.

	Skill-builder-data	ADM-2024
BKT	0.65478	0.68846
IBKT	0.91653	0.74618
MF-IBKT-No-Encoder	0.93577	0.83984
MF-IBKT-Use-Encoder	0.94058	0.86361

The model Acc performance is shown in Table 3.In the skill-builder-data dataset,the Accuracy of BKT and IBKT reaches 0.70062,0.74092,and the Accuracy of IBKT-MFIBKT-MF-No-Encoder and IBKT-MF-Use-Encoder reaches 0.7717 and 0.78121.In the dataset ADM-2024,the Accuracy of BKT,IBKT is 0.618,0.64675,IBKT-MF-No-Encoder and IBKT-MF-Use-Encoder reaches 0.70832,0.72168.

Table 3. Model Acc performance.

	skill-builder-data	ADM-2024
BKT	0.70062	0.618
IBKT	0.74092	0.64675
MF-IBKT-No-Encoder	0.7717	0.70832
MF-IBKT-Use-Encoder	0.78121	0.72168

As can be seen from Tables 2 and 3, both AUC and Accuracy of IBKT are improved compared with BKT. Its AUC performance improvement is most obvious in the skill-builder-data dataset. This indicates that IBKT utilizes the nonlinear fitting property of neural networks and the forgetting property of LSTM to improve the accuracy of predicting learners' knowledge states. The AUC and Accuracy of the IBKT-MF algorithm are also improved when multiple learning features are fused, but no self-encoder is added, where the AUC has the best prediction performance in the skill-builder dataset, up to 0.93577, and the best improvement effect in ACM-2024. In order to improve the algorithm's computational performance and to explore the potential connection between each learning feature, the IBKT-MF algorithm in this paper incorporates a self-encoder in addition to fusing multiple learning features. After dimensionality reduction with the self-encoder, the learning information is not lost, and the AUC and Accuracy are improved.

The performances of different types of IBKT algorithms during the training process in the two datasets are shown in Figs. 3 and 4, respectively. It is found that the AUC improvement effect of IBKT-MF is stable. In summary, the IBKT-MF algorithm meets the expected effect and is able to realize the knowledge state assessment function in the smart adaptation system.

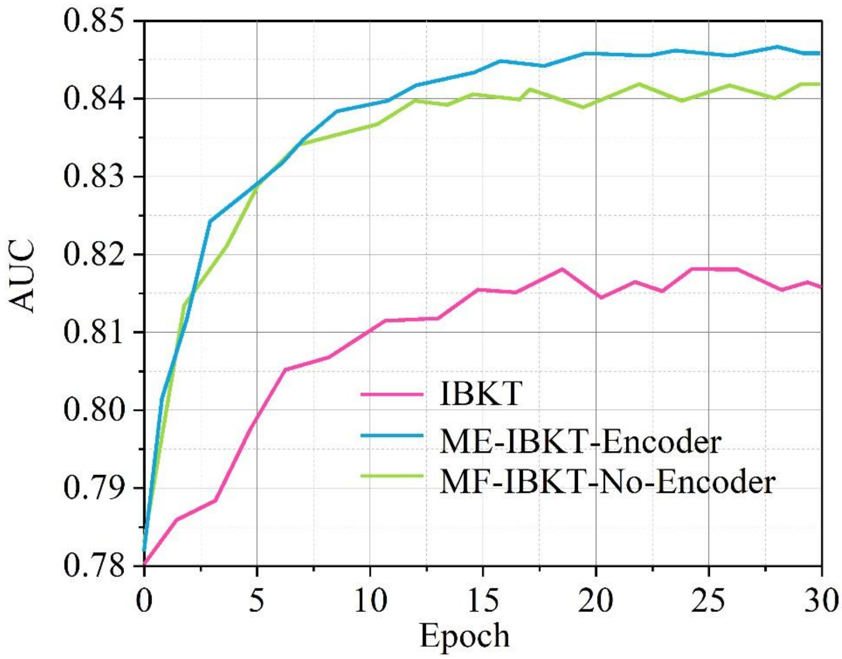

Figure 3. Different models are used in the skill-builder-data.

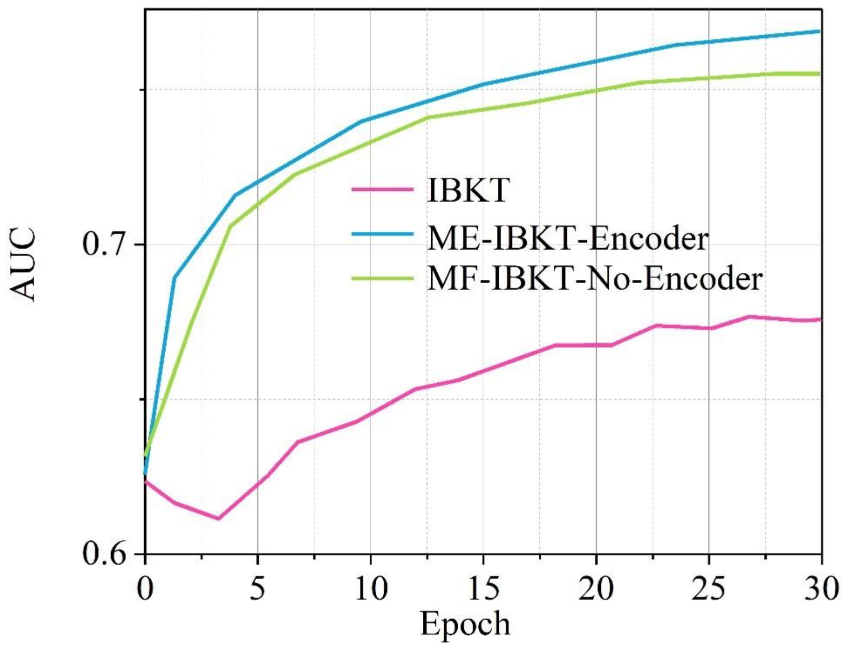

Figure 4. Different models are used in the adm-2024 data concentration.

4. Question-and-answer interactive system based on the level of students' knowledge of Civics and Party building

4.1. GRU Layer

Let's review the model of LSTM, the hidden layer of LSTM has a complex structure, it implements three gate structures, i.e., the forget gate, the input gate and the output gate.LSTM was proposed to overcome the problem that RNN could not deal with the remote dependency very well, and GRU is a variant of LSTM, of course, there are many other variations of LSTM.GRU maintains the effect of LSTM while making the structure simpler, so it is also a very popular neural network model.

The structure of GRU is shown in Fig. 5, which combines the input and forget gates of LSTM into a single update gate, along with some other changes. Since there is one less control gate compared to

LSTM, it will have fewer parameters and converge faster.

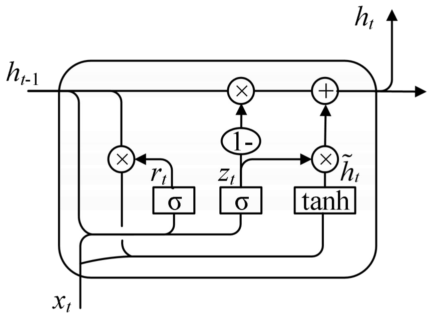

Figure 5. The structure of GRU.

Assume that the input sequence $x=\{x_1,x_2,x_3,...x_t\}$, x_t denotes the word vector of the input at moment t, the output of the hidden layer at the previous moment is h_{t-1}, z_t is the updating gate, and r_t is the reset gate, then the states inside the GRU are as follows:

Update gate:

$$z_t=\sigma\left(W_z\cdot[h_{t-1},x_t]\right) \tag{10}$$

Reset the door:

$$r_t=\sigma\left(W_r\cdot[h_{t-1},x_t]\right) \tag{11}$$

Internal state at the moment of t:

$$\widetilde{h}_t=\tanh\left(W_h\cdot[r_t*h_{t-1},x_t]\right) \tag{12}$$

t moment output:

$$h_t=(1-z_t)*h_{t-1}+z_t*\widetilde{h}_t \tag{13}$$

Predictive Output:

$$y_t=\sigma\left(W_o\cdot h_t\right) \tag{14}$$

Where * denotes pointwise (point-by-point multiplication) operation, σ denotes sigmod activation function, and W denotes weight matrix. In order to prevent overfitting, a dropout is added here during training, and it can be seen that the effective information can be retained for a longer distance through the control gate of the GRU.

4.2. Bidirectional Threshold Cycle Unit

The unidirectional GRU can only get the context information up to the current moment and it would be more helpful for the sequence task if it can get the context information after the current moment. Therefore, here the unidirectional GRU in it is replaced by a bidirectional GRU, which is based on the idea of using two GRU layers to input the input sequence from forward and reverse direction respectively. At each moment t, the inputs are provided to both GRUs in opposite directions, and the output is a new vector that is spliced together from the outputs of the two GRUs.BiGRU allows more semantic information to be included in each vector representation compared to unidirectional GRUs, which results in better quality features. The structure of the bi-directional GRU model is shown in Figure 6.

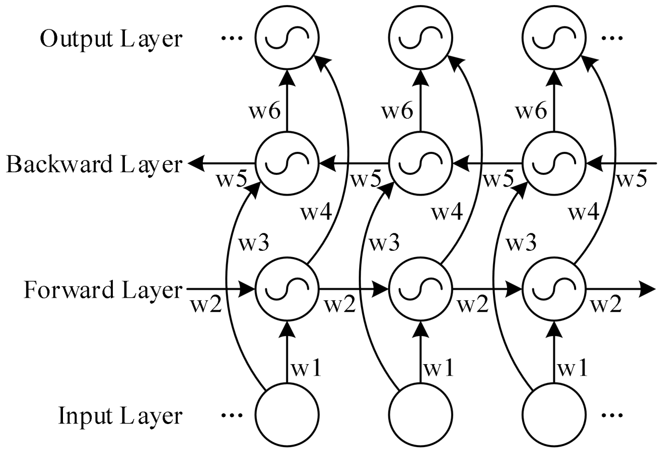

Figure 6. Bidirectional GRU model.

4.3. Attention mechanisms

Attention mechanism has achieved excellent results in recent years in the direction of machine translation, image labeling synthesis and natural language understanding, etc. Soft Attention mechanism is to find the probability distribution of attention allocation, for any word in the input sentence X is given a probability, or attention weight coefficients. Different words are assigned different weight coefficients, which reflect different levels of semantic importance. There are two sources of input to the attention mechanism that we have added, one is the hidden layer vector h_m^Q on the encoding side, and the other is the hidden layer state vector h_{l-1}^A on the decoding side [24], and after a weighted average summation of the attention weight coefficients we can get the context vector z_l with the following formula:

$$P_{lm} = v^T \tanh\left(Wh_{l-1}^A + Uh_m^Q\right) \tag{15}$$

$$\vartheta_{lm} = \frac{\exp(P_{lm})}{\sum_{m=0}^{M} \exp(P_{lm})} \tag{16}$$

$$z_l = \sum_{m=0}^{M} \vartheta_{lm} h_m^Q \tag{17}$$

4.4. Neural network model based on BiGRU-Attention

After the previous introduction, we can get a neural network model based on BiGRU-Attention, and the structure of BiGRU-Attention model is schematically shown in Fig. 7.

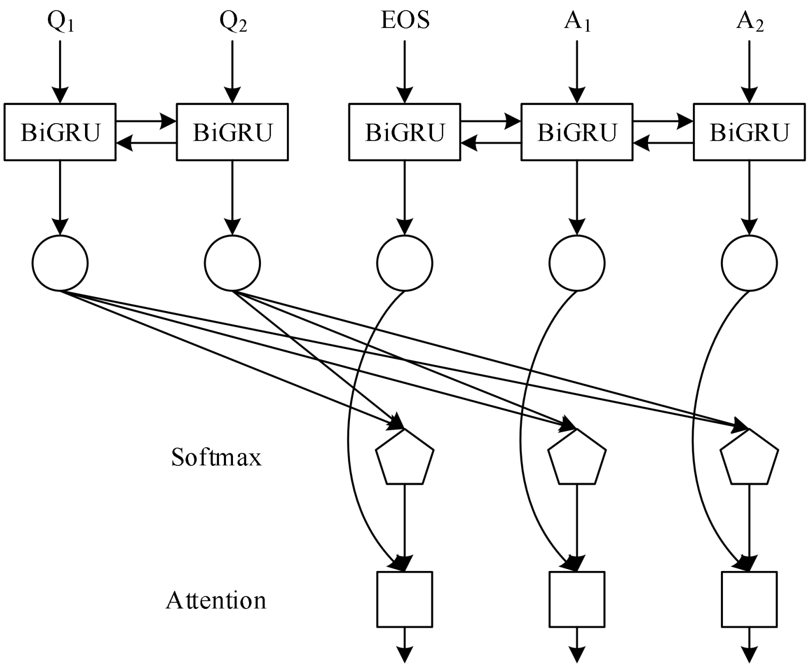

Figure 7. Schematic diagram of the BiGRU-Attention model structure.

5. Effectiveness of pedagogical interaction based on student-level question-and-answer interaction systems

5.1. Q&A system performance testing

5.1.1. Construction of data sets

The semantic similarity model requires a large number of labeled datasets for model training, and the datasets used in this experiment are two LCQMCs and a self-constructed computer course knowledge dataset.

LCQMC is an open domain Chinese dataset of sentence matching constructed based on Baidu Knowledge, which has a large data volume of 260166 labeled data and high data quality, and has become a basic dataset for Chinese NLP tasks. The construction process is as follows: Crawlers crawl the Baidu Knowledge website to capture relevant questions about course knowledge, and at the same time capture the similar questions corresponding to each question. For the construction of positive samples, each question and its corresponding similar question are labeled as similar, and for the construction of negative samples, each question and other questions are labeled as dissimilar. The experiment divides the dataset into training set, validation set and test set in the ratio of 7:2:1.

5.1.2. Model parameterization

In the word embedding layer, Google's word2vec is used to pre-train the word vectors, and the dimensionality of the vectors is 300 dimensions. Three kinds of convolutional kernels are set up, the window size is 1,2,3 respectively, the number of convolutional kernels is 150, the number of hidden nodes in LSTM layer is 131, and for the optimizer, the Adam optimizer is chosen to update the parameters of each layer of the network by back propagation. The learning rate is set to 0.01, and in order to prevent overfitting, drop-out is added to each layer, and the value of the parameter is set to 0.5.During the whole training process, the parameters are updated by using small batch gradient descent, the size of the small batch is 1036, and the number of training rounds is set to 50.

5.1.3. Experimental results and analysis

In this experiment, CNN-based semantic similarity matching model, LSTM-based semantic similarity matching model and the model proposed in this topic are selected for comparison. The comparison results of each model under different datasets are shown in Table 4.

Table 4. Comparison results of various models under different datasets.

	Self-built dataset		LCOMC dataset	
Model	Accuracy rate	F1 value	Accuracy rate	F1 value
CNN	0.678	0.693	0.707	0.756
LSTM	0.745	0.734	0.731	0.779
Ours	0.81	0.845	0.824	0.843

The following conclusions can be obtained by analyzing the experimental results.

(1) The training effect of the three models on the LCQMC dataset is better than the effect of training on the self-constructed dataset, which may be due to the fact that there is some error in labeling the data when constructing the computer course knowledge dataset.

(2) In terms of accuracy and F1 value, it can be seen that the LSTM-based model has higher accuracy and F1 value than the CNN-based model, and LSTM is slightly better than CNN in this natural language processing task, while the accuracy and F1 value of the model based on CNN and LSTM with attention mechanism are higher than that of the model using a single model.

In summary, both on the self-constructed dataset and on the LCQMC dataset, in terms of the two evaluation metrics of accuracy and F1 value. The training effect of the model proposed in this paper is better than the CNN-based model and the LSTM-based model.

5.2. Intelligent Quiz Performance Testing

In this paper, we use simulated questioning to test the accuracy and efficiency of the Q&A system model for the Civics and Politics course that integrates party building knowledge, and verify whether it can provide users with relatively high-quality knowledge services. In this paper, we invite a number of volunteers with Python learning experience or Python language experience to ask questions to the intelligent Q&A applet, simulate the actual user questioning scenarios, and record the entire user questioning process, so as to perform statistics and calculations on relevant data and indicators. The test indexes mainly include: the type of Civics question, the number of Civics questions, the number of correct answers, the Civics question answer rate, and the average response speed. The performance test of the Q&A applet is shown in Table 5. As can be seen from the table, a total of 305 question records were collected in this simulated question test, with an average answer rate of 81.31% and an average response time of 1.29 seconds, which basically meets the requirements of providing users with high-quality knowledge services. The Q&A system model has a high accuracy rate for the types of questions preset in this paper.

Table 5. Performance testing.

Question type	Number of Questions	Number of correct answers	Accuracy rate of question answering(%)	Average response speed(s)
"definition"	24	21	87.50	1.3
"Function"	68	60	88.24	1.2
"type"	29	24	82.76	1
"structure"	25	19	76.00	1.1
"Operation step"	21	18	85.71	1
"Writing rules"	37	33	89.19	1.2
"characteristics"	12	10	83.33	1.1
"Method"	53	47	88.68	1.5
"Other"	36	16	44.44	2.2
Total	305	248	81.31	1.29

5.3. Interactive Analysis of Civics Classroom Teaching by Integrating Party Building Knowledge

This section of the experiment carries out a teaching behavior analysis experiment using teachers and students in a Civics classroom that integrates party building knowledge in a university as the research subjects.

5.3.1. Behavioral Sequence Analysis of Teachers and Students

The behavioral changes of teachers and students in the Civics classroom of integrating party building knowledge are shown in the form of line graphs, the horizontal axis indicates the sequence number of the intercepted pictures, and the vertical axis indicates the category of the behavior, which can be clearly seen in a lesson in the behavior of the time when there is a large number of behavioral changes of teachers and students as shown in Fig. 8, which shows that in the first half of this lesson, the teacher mainly teaches the Civics classroom of integrating party building, and students raise their hands or stand up to answer questions and discuss, and the interaction between teachers and students is relatively good, and then students begin to read exercises. Students raised their hands or stood up from time to time to answer questions, and also had discussions, the interaction between teachers and students was relatively good, and then students began to read the exercises. The second half of the program repeats the first two states.

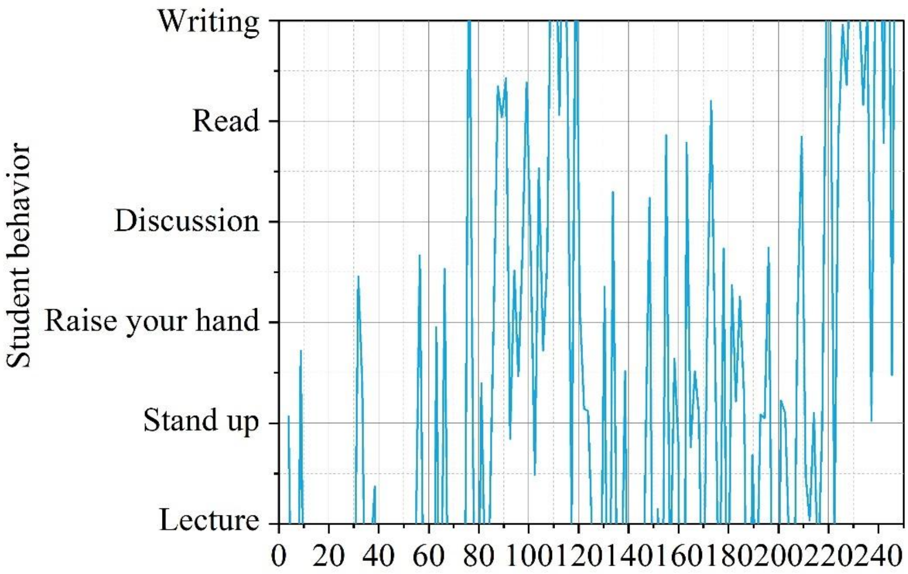

Figure 8. Changes in the behaviors of teachers and students.

Using lagged sequence analysis the frequency and residual values of the behavioral sequences of teachers and students in the two Civics classrooms integrating party building knowledge appear as shown in Tables 6 and 7, respectively.In the two classrooms combined, the frequency of the behavioral sequence of Lecture-Lecture is the most frequent, indicating that the teacher's teaching lasts longer.Among the behavioral sequences of the different behavioral transitions,Lecture-Rise is the most frequent, indicating that the interaction between the teacher and the students is relatively good. By checking the table of adjusted residual values, it was found that the highest was writing-reading with a residual value of 0.663, mainly because the number of behaviors was small, which did not constitute significance, accompanied by the fact that lagged sequences could be analyzed again after several classroom teaching teacher-student behavior detection and identification.

Table 6. The frequency of behavioral transitions between teachers and students.

	Raise your hand	Writing	Discussion	Lecture	stand up	Read
Raise your hand	15	1	1	22	9	1
Writing	3	22	1	9	8	2
Discussion	0	0	1	2	2	0
Lecture	15	5	5	131	37	12
stand up	11	15	1	36	85	3
Read	2	4	0	10	1	14

Table 7. The adjusted residual value.

	Raise your hand	Writing	Discussion	Lecture	stand up	Read
Raise your hand	4.911	-2.23	0.455	0.153	-1.228	-1.236
Writing	-1.125	8.606	-0.866	-3.706	-0.903	0.663

Discussion	0.643	-0.784	3.128	-0.444	0.12	-0.662
Lecture	-0.539	-3.834	0.041	7.697	-4.563	-1.7
stand up	-1.615	-0.025	-0.157	-5.194	8.099	-2.762
Read	-0.606	0.601	-0.708	-1.28	-3.52	9.403

5.3.2. Real-Time Engagement Analysis of Student Behavior

Since there are 8 kinds of student behavior classifications used in this study, and there are 7 kinds of student behavior engagement indexes developed in general, the real-time engagement indexes of student behaviors are shown in Table 8, and this study has an additional class of "looking down at the book (reading)" behavior, so 50 students majoring in Civic and Political Education were recruited to rate the engagement degree of 10 images showing different numbers of "looking down at the book (reading)" behaviors, and the scores of all the raters were divided into four levels. So 50 students majoring in Civic and Political Education were recruited, and the 10 images showing different numbers of "looking down (reading)" behaviors were scored in terms of engagement, and the scoring criteria were divided into four grades, and the scores of all the scorers were analyzed by SPSS, and the Cronbach coefficient of the 50 scorers was 0.862, which indicated that the scores of all the scorers were in a high degree of agreement, and the scores were averaged and normalized. The scores were averaged and normalized, and the final input degree of "looking down (reading)" behavior was 0.8.

Table 8. Real-time student behavior engagement scoring index.

Student behavior in this article	Student behavior in general circumstances	Input degree (normalized)
Listen	Listen	0.5
Lower your head and read a book		0.8
Read Aloud	Read Aloud	0.92
stand up	Speech	0.83
Raise your hand	Raise your hand	1
Writing	Writing	0.92
Discussion	Discussion	0.77
The behavior of not listening to lectures	Inattentive behavior	0

The change curve of students' behavioral real-time engagement is shown in Fig. 9, from which it can be seen that students' real-time engagement is still high and stable most of the time.

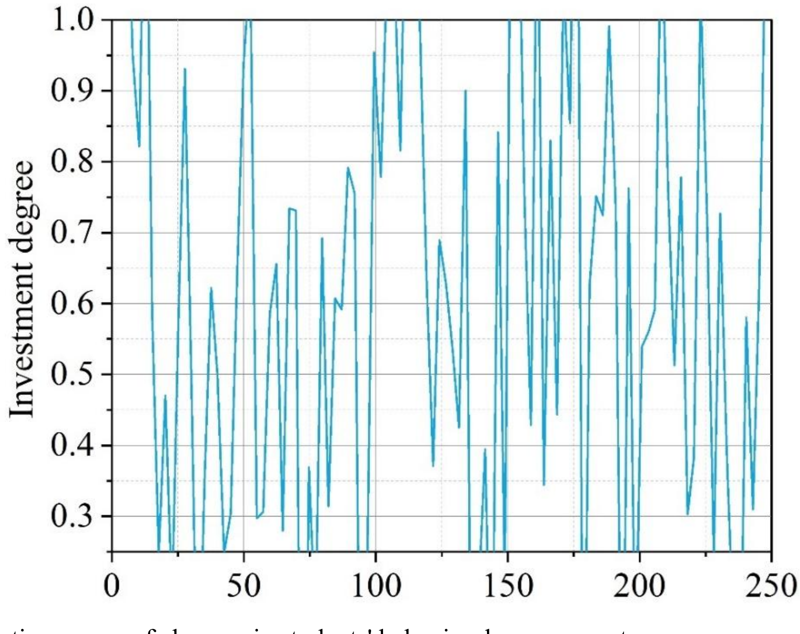

Figure 9. Real-time curve of changes in students' behavioral engagement.

5.3.3. Comparative Analysis of Civics Classrooms with Different Integration of Party Building Knowledge

The two different classes were respectively analyzed and counted for behavior, student A used the method of this paper for Civics learning, and student B used the traditional method for Civics learning, and then the two kinds of data were compared, and the comparative curve of the change of students' behavioral real-time engagement degree was shown in Fig. 10, and it can be found that the behavioral real-time engagement degree of students in classroom A, which is represented by the blue curve, is higher than the behavioral real-time engagement degree of students in classroom B, which is represented by the pink curve. The behavioral real-time engagement of students in classroom A represented by the blue curve is higher than that of students in classroom B represented by the pink curve.

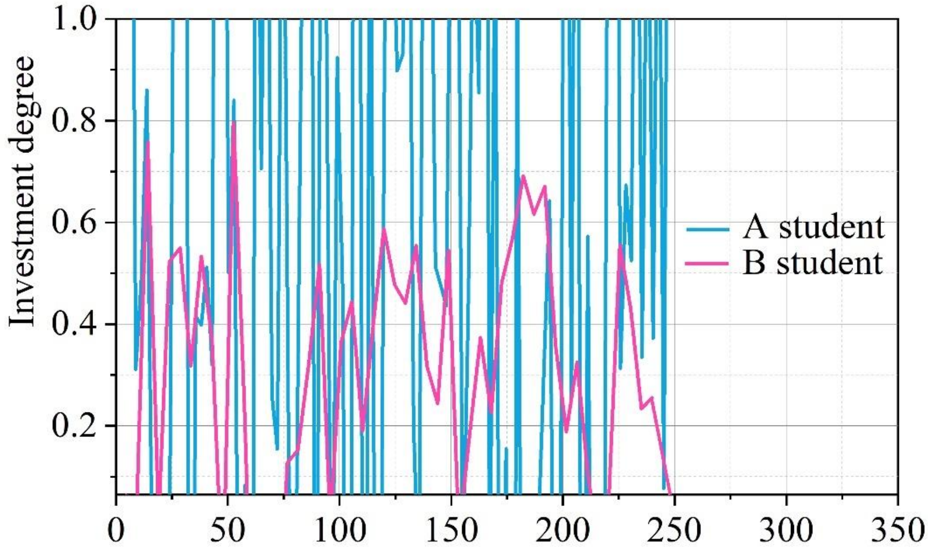

Figure 10. Student behavior real-time input change curve.

6. Conclusion

This paper designs and implements a question and answer system based on students' knowledge level to help teachers and students realize accurate teaching, in order to explore the teaching interaction mode and effect of the synergistic development of Party building and Civic and Political Education in colleges and universities. The conclusions drawn from the article are:

(1) After testing on the public dataset, the AUC of the student knowledge point tracking model can reach up to 0.93577, and the model performance is stable and the accuracy can meet the practical application.

(2) Through the performance test of the Q&A system model, it is found that the average answer rate of the model is 81.31%, and the average response time is 1.29 seconds, which can meet the requirements of providing users with high-quality knowledge services.

(3) By analyzing and counting the behaviors of two different Civics classes, it is found that the students' behaviors of Civics learning using the method of this paper are more engaged in real time.

In summary, the method of this paper can analyze the interactive effect of teaching Civics and Politics classroom by integrating Party building knowledge and help to improve the classroom effect. The research results can provide certain reference for the innovation and development of the teaching interaction mode of the synergistic development of party building and Civic and Political education in colleges and universities.

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