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Design and Implementation of Interdisciplinary Knowledge Integration and Teaching Innovation System for Dual Colleges and Universities Based on Artificial Intelligence Algorithms

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ABSTRACT

The all-round penetration of artificial intelligence technology has brought about a drastic change in the educational landscape, and the teaching system of colleges and universities relies on artificial intelligence technology to expand its own boundaries, leading to interdisciplinary knowledge fusion between dual colleges and universities. With the support of AI technology, a teaching system design idea of interdisciplinary knowledge integration is proposed, and a teaching innovation system of interdisciplinary knowledge integration between dual colleges and universities is established. Taking the learners' interdisciplinary knowledge point response situation as an entry point, input modeling is carried out for the learners' interdisciplinary knowledge points, forgetting coefficient, etc., and the dual colleges' interdisciplinary knowledge tracking SA-BiGRU model is established by combining BiGRU and the attention mechanism, and simulation verification is carried out to verify its effectiveness. Taking a vocational college in province G as an example, a dual college interdisciplinary teaching comparison experiment was designed in combination with the teaching innovation system, so as to verify the effectiveness of the interdisciplinary knowledge integration teaching innovation system. The results show that the AUC and ACC of the SA-BiGRU model can reach up to 0.837 and 0.841 respectively in interdisciplinary knowledge tracking, and the learners' interdisciplinary knowledge reserve and ideological literacy level have been improved by 1.36 and 1.82 points respectively compared with that before the experiment. Relying on artificial intelligence technology can promote interdisciplinary knowledge integration, provide a new research direction for the development of interdisciplinary intelligence in BiGR, and lay the foundation for the cultivation of highly skilled and qualified applied talents.

Keywords: artificial intelligence, BiGRU; attention mechanism, SA-BiGRU model, interdisciplinary knowledge integration

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1. Introduction

With the rapid development of society, artificial intelligence has become a necessary core technology in all walks of life, and in the field of education, the application of artificial intelligence is also becoming more and more extensive, especially in interdisciplinary knowledge integration and teaching [1-2].

Interdisciplinary knowledge integration is to combine different subject knowledge with each other to form a unified and organic whole, which can improve students' learning effect and comprehensive quality [3-4]. Interdisciplinary knowledge integration can cultivate students' comprehensive thinking and innovation ability, so that students can flexibly use the knowledge of various disciplines to solve practical problems [5]. In addition, interdisciplinary knowledge integration can also deepen the understanding and memory of subject knowledge, broaden the knowledge base, and cultivate students' self-learning ability and lifelong learning consciousness [6-8]. Interdisciplinary teaching refers to the integration of knowledge from different disciplines for teaching, which has many advantages compared with traditional single-discipline teaching [9-10]. It can increase students' interest and initiative in learning, Xi interdisciplinary teaching can stimulate students' curiosity and inquisitiveness, provide more possibilities and challenges in the learning process, and thus motivate students to actively participate in learning [11-13].

In addition, interdisciplinary teaching can cultivate the comprehensive quality of students, by combining the knowledge of multiple disciplines with each other, students can obtain a more comprehensive knowledge system and skills, and improve the ability of comprehensive analysis and comprehensive problem solving [14-17]. And the application of artificial intelligence leads the development of the integration of disciplinary knowledge and teaching, and builds a diversified knowledge system [18]. Through AI technology, the knowledge of different disciplines can be integrated with each other to cultivate students' comprehensive ability and innovative thinking [19-20]. At the same time, personalized learning programs and teaching design can help students better adapt to learning and growth, and teachers can also use AI technology for teaching design and assessment to improve the quality and effectiveness of teaching [21-24].

With the promotion of artificial intelligence technology, the integrated teaching of dual colleges and universities is gradually realizing the transformation from traditional teaching to refined, interdisciplinary integration and innovative teaching. On the basis of sorting out the concepts related to the construction of dual colleges and interdisciplinary knowledge integration, the article introduces the idea of designing interdisciplinary teaching system supported by artificial intelligence technology. Then, taking learners' mastery of interdisciplinary knowledge points as the target of knowledge tracking task, and taking knowledge point correlation coefficient, forgetting coefficient, and knowledge reserve as inputs, the SA-BiGRU model applied to interdisciplinary knowledge tracking is constructed by utilizing BiGRU and attention mechanism. Two parallel classes of students majoring in mechatronics in a vocational college are taken as research objects to explore the application effect of the interdisciplinary knowledge integration teaching system supported by artificial intelligence.

2. Bi-university interdisciplinary knowledge integration and teaching system

With the rapid development of big data and artificial intelligence technologies, the field of education is experiencing unprecedented and profound changes. These emerging technologies not only change the way of knowledge dissemination, but also reshape the structure and mode of teaching, prompting education from the traditional single-discipline teaching to the direction of interdisciplinary integration and development. Dual colleges and universities need to make full use of artificial intelligence technology to empower the integration of interdisciplinary knowledge, so as to better realize the realization of the goal of high-level and high-quality "double-high", and to lay a solid foundation for talent cultivation, disciplinary development, and pedagogical innovation.

2.1. Bi-university interdisciplinary knowledge integration

2.1.1. Bi-university construction. The purpose of the construction of "dual colleges and universities" is to build a group of higher vocational schools and backbone specialties (clusters) for China's education and modernization that can lead vocational education reform, promote vocational education development, have Chinese characteristics, adapt to the development needs, and are close to the world level, leading to the deepening of the reform of vocational education in a sustained manner, and promoting the upgrading of industries and high-quality development. From the point of view of the goal of "dual colleges and universities" construction, vocational education is related to the comprehensive quality of nationals and the overall improvement of skill level, and can respond to the current economic development speed and industrial structure of the dual-orientation of demand. In the face of the current situation that more industrial workers are needed for the transfer of industrial chain, vocational education has become a breakthrough for cultivating professional and technical personnel.

The significance of promoting the construction of "dual colleges and universities" mainly consists of the following four aspects:

1) It is conducive to enhancing the support of schools in the national strategy. China's economic and social construction requires a large number of high-quality human resources, which urgently requires schools to comprehensively improve the quality of personnel training through the construction of dual colleges and universities.

2) It is conducive to enhancing the school's local demand. Through docking local industries, a number of local economic and social development urgently needed in the field of shortage of high-quality technical and skilled personnel training and training bases have been built. Provide a talent dividend for economic and social development, and provide strong talent support for the formation of important economic growth poles in the region.

3) It is conducive to enhancing the recognition of the school's industry. Through the completion of a number of specialized fields of technical skills innovation service platform, to provide different types of talents for different industries, to create new efficiency growth points, so that the industry and enterprises are recognized.

4) It is conducive to enhancing the degree of international exchange of schools. By exploring the new mode of opening up of vocational education to the outside world with the promotion and training of special skill standards, international talent training, and international talent cultivation as a breakthrough, the influence of the school in opening up to the outside world will be enhanced.

2.1.2. Integration of interdisciplinary knowledge. At present, there is no unified understanding of the concept of "interdisciplinary knowledge integration", and there are similar expressions such as "interdisciplinary", "collaborative teaching", "disciplinary integration" and "disciplinary infiltration". Even though these concepts have different emphases, they all emphasize the integration of teaching or scientific research activities in two or more disciplines with the common goal of improving teaching effectiveness [25].

By integrating the existing relevant research literature, this paper can understand the integration of interdisciplinary knowledge as a kind of teaching activity that breaks down disciplinary barriers and integrates theories and methods of different disciplines. The term "integration" here is not a mechanical listing and repetition of knowledge from different disciplines, but an effective integration that comprehensively considers the actual situation and the characteristics of core disciplines. "Interdisciplinary knowledge integration" has two directions, one is to the comprehensive teaching under the interdisciplinarity, and the other is to the in-depth teaching of the study of interdisciplinary laws. Some scholars have pointed out that interdisciplinarity includes the dominant discipline and other disciplines, the dominant discipline is the object and goal, and the other discipline is the method and technique. In order to achieve interdisciplinary integration, it is necessary to give full play to the benefits and roles of different discipline resources, which is conducive to promoting learning cognition, improving the quality of subject teaching, and enhancing the comprehensive quality of students, so as to improve the learning efficiency of students and help the high-quality construction and high-level development of the two universities.

2.2. Design of interdisciplinary teaching system

2.2.1. Instructional design ideas. In the construction process of dual colleges and universities, artificial intelligence technology-oriented can give interdisciplinary knowledge integration a more complete path, and also provides new ideas for the innovative design of interdisciplinary teaching system in dual colleges and universities. The application of artificial intelligence technology in the interdisciplinary integration teaching design of dual colleges and universities requires full consideration of the setting of teaching objectives, teaching content and teaching evaluation.

In terms of teaching objectives, emphasis should be placed on hierarchy and multidimensionality, i.e., each student should have the corresponding level of teaching objectives, and at the same time, the teaching objectives should be described in detail from the four aspects of disciplinary core literacy or the three dimensions of knowledge and skills, process and methodology, and affective attitudes and values. In terms of teaching content, the relevance between two or more disciplines should be considered and the practical nature of inquiry learning should be emphasized. In terms of teaching evaluation, attention should be paid to the interdisciplinary nature of the evaluation content and the diversification of the approach, while giving play to the guiding role of evaluation. To be problem-oriented, the problem should come from the real situation, and teachers should stimulate students' inquiry ability. Through the four processes of “project introduction→project analysis→project implementation→project summary”, students are guided to acquire relevant knowledge and skills of multiple disciplines through solving project problems, and then cultivate students' ability to transfer knowledge of disciplines, innovation and practical ability.

2.2.2. Design of the teaching system. Guided by the construction goals of dual colleges and universities, and with the effective empowerment of artificial intelligence technology, this paper proposes a teaching system framework for interdisciplinary knowledge integration in dual colleges and universities, the specific content of which is shown in Figure 1. It mainly contains three levels and four modules, which can well help students use multidisciplinary knowledge to explain and solve various phenomena in their professional fields.

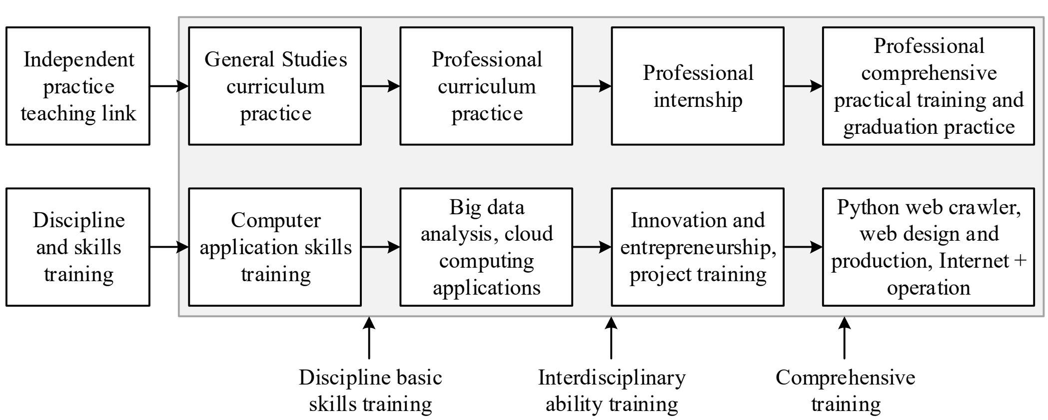

Fig. 1. The teaching system of interdisciplinary knowledge fusion

The three levels include professional basic skills training, interdisciplinary skills training and comprehensive training to reflect the training process from professional basic to interdisciplinary to comprehensive application. The professional basic skills training focuses on the experimental teaching of the courses and the application of quantitative methods. Cross-disciplinary skills training focuses on cultivating students' ability to apply multidisciplinary knowledge to solve practical problems. Comprehensive training includes professional apprenticeship, graduation internship, graduation thesis, entrepreneurial ideas, innovation and entrepreneurship project recognition, career development and employment guidance. Through the recognition of innovation and entrepreneurship projects, students are trained to face the fast-changing market environment and comprehensively utilize the knowledge they have learned to make management decision simulation, so as to cultivate students' interdisciplinary professional ability.

The four modules include in-class laboratory teaching, independent practical teaching, social practical activities and extracurricular scientific and technological activities. Through rational design and implementation of in-class experimental teaching, students can better understand and apply the theoretical knowledge they have learned through experimentation, observation and operation, and improve their learning interest and motivation. At the same time, in-class experimental activities also help to cultivate students' sense of cooperation and team spirit, and improve their communication and collaboration skills. Through participating in extracurricular scientific and technological activities such as scientific innovation, scientific research competition and discipline research, students can develop their innovative thinking and practical ability, deepen their understanding and practical application of subject knowledge, and expand their academic fields.

3. Interdisciplinary Knowledge Tracing and Instructional Design in Dual Colleges and Universities

Interdisciplinary teaching refers to a teaching method in which teachers go beyond certain fixed procedures of knowledge accumulation and guide students to learn more important and newer knowledge according to the level, needs and possibilities of students' physical and mental development. In the process of interdisciplinary knowledge integration in dual colleges and universities, how to accurately grasp students' knowledge changes and knowledge mastery has become a key research issue to enhance interdisciplinary integration teaching. The knowledge tracking model based on deep learning technology, combined with the students' evolution in interdisciplinary knowledge, can accurately grasp the students' mastery of knowledge points, and provide effective decision-making support for optimizing the interdisciplinary knowledge integration teaching method.

3.1. Problem definition and input modeling

3.1.1. Problem definition. In a knowledge tracking task, the answer record completed by each learner is usually defined as X_t, and the set of exercise numbers is defined as $|E|$. In the answer record of the dataset, the embedding of an exercise answered by a learner at a certain moment t is denoted as $x_i \in D$, and the embedding of the answer record is denoted as the <exercise, answer> tuple $(e_t, r_t) \in D$ [26]. Where D denotes the dimension of the embedding representation, $e_t \in E$, represents the serial number of the exercise question answered by this learner at moment t, and r_t denotes the result of the learner's answer regarding the exercise question e_t, where a correct answer results in $r_t = 1$, and vice versa, and a wrong answer results in $r_t = 0$. Therefore, the sequential learning task of this learner before moment t can be expressed as $X_t = [(e_1, r_1), (e_2, r_2), \ldots, (e_t, r_t)]$. By modeling the learner's question answering, the implied knowledge state is then extracted and the change of the knowledge state over time is tracked. Since the assessment of the knowledge state cannot be externalized though, the formula commonly used in existing knowledge tracking tasks to represent the probability of predicting the learner's correctly answering an exercise at the next moment can be expressed as:

$$P(r_{t+1}=1 \mid e_{t+1}, X_t) \tag{1}$$

Based on the above description of the knowledge tracking task, the problem addressed in this paper is defined as follows:
1) Model the changes in the knowledge state of this learner based on the learner's history of doing exercises.
2) Predicting the answer result r_{t+1} of this learner on the next exercise e_{t+1} and comparing it with the actual result to judge the accuracy of the model prediction.

3.1.2. Input modeling. In order to capture the relevance of interdisciplinary knowledge to previous disciplinary knowledge and to consider the effect of forgetting factors, this paper treats metadata as the relevant definitions and their computational processes required for model information embedding. It is specified as follows:
1) Knowledge point information e_i. e_i is the knowledge point category and position vector sum of the i th knowledge point given to the student. First the function $f: M \to R^d$ is learned using the word embedding technique, where the textual content is represented as an embedding matrix and f is a parameterized function that maps words to a d -dimensional distribution vector. Secondly, the semantic representation of each link is learned from the textual content of the exercise, and the embedding of the knowledge point e_i can be represented as:

$$e_i = \frac{1}{|s_i|}\sum_{w \in s}\frac{a}{a+p(w)}f(w) \tag{2}$$

where a is a trainable parameter; s_i is the i th practice text; and $p(w)$ denotes the probability of word w.
2) Matrix of knowledge point correlation coefficients $A_t(i)$. Potential relationships between knowledge points are explored and correlation coefficients are calculated from students' previous interactions, and the two features of the inferred relationship coefficients are the performance of students making knowledge points and the textual content of the knowledge points. The two features of the relationship coefficients are the students' performance in answering the knowledge point and the textual content of the knowledge point, where the knowledge gained from answering the knowledge point j can be inferred to be helpful for the knowledge point i. The semantic similarity between two knowledge points can be inferred from the textual content of the knowledge point.

In order to evaluate the correlation between the knowledge point e_t to be answered currently and the previously practiced knowledge point e_i, the correlation coefficient $w_t(i)$ is computed by activating the masked dot product between e_t and e_i via SoftMax. Then:

$$\begin{cases} r_t(i) = Masking(e_i o e_t) & i \in (t, N) \\ w_t(i) = Softmax(r_t(i)) & i \in (1, N) \end{cases} \tag{3}$$

where the response information $r_t(i)$ represents the student's response to e_i. If the student's i th response is correct then $r_t(i)=1$, if it is not correct then it is 0. $Softmax(r(i)) = \exp(r(i)) / \sum_{i=1}^{N}\exp(r(i))$, and the Masking function is used in order to exclude the learning records after the current moment.

Next, the textual similarity between the knowledge point e_t and the previously practiced knowledge point e_i is calculated by the Cosine function. To wit:

$$sim_{t(i)} = \frac{e_t e_i}{\|e_t\|_2 \|e_i\|_2} \tag{4}$$

Finally, calculate the relationship between the knowledge point e_t and the knowledge point e_i, i.e:

$$A_t(i) = \begin{cases} w_t(i) + sim_t(i) & \text{if } w_t(i) + sim_t(i) > \theta \\ 0 & \text{otherwis} \end{cases} \tag{5}$$

where θ is the threshold for controlling the sparsity of the relation matrix.

3) Knowledge base R^K. There is a correlation between the knowledge points, based on the previous answers to the relevant questions can assess both the correct rate of similar knowledge points, but also to assess the student's reserves of such knowledge, through the relationship coefficients matrix between the knowledge points can know which knowledge points are similar. In order to measure the students' mastery of knowledge concepts related to the current answer to the knowledge point, the correct rate of answering knowledge points related to such knowledge points is calculated and used as the knowledge reserve coefficient R_t^K, which can be expressed as:

$$R_t^K(m) = \frac{\sum_{i=0}^{i-1} a_j^m = 1}{count(e^n)} \quad \text{if } (A_t(i) \neq 0) \tag{6}$$

where $m \in (1, M)$, denotes the number of knowledge points associated with knowledge point i; $count(e^m)$ is the number of times the knowledge point i has been answered, $\sum_{i=0}^{t-1} a_j^m == 1$ is the number of times that the knowledge points related to the knowledge point i have been answered correctly, and the final rate of correctness is the indicator of the knowledge reserve, $R_t(m)$. The larger value indicates better mastery.

4) Forgetting coefficient R^T. The time interval between learning interactions is an important factor that affects the complex changes in the learning process, as time passes students in the past will forget what they have learned. In order to simulate the students' mastery of knowledge points as the time interval increases, a curve with exponential decay over time is designed based on the idea of forgetting curve theory. Given a time sequence of student interactions $t = (t_1, t_2, \cdots, t_{n-1})$ and the time of the student's next practice t_n, the time interval is $\Delta_i = t_n - t_i$. Then the forgetting coefficient is:

$$R^T = [\exp(-\Delta_1 / S_u), \exp(-\Delta_2 / S_u), \cdots, \exp(-\Delta_{n-1} / S_u)] \tag{7}$$

where S_u denotes the strength of the student's memory, which can be obtained through training.

3.2. Interdisciplinary Knowledge Tracking Model

3.2.1. SA-BiGRU modeling. In order to better access learners' knowledge mastery in the process of interdisciplinary knowledge integration, this paper introduces BiGRU and attention mechanism to establish the SA-BiGRU model for tracking learners' interdisciplinary knowledge evolution, and the framework of the SA-BiGRU model is shown in Figure 2. The SA-BiGRU model proposed in this paper optimizes the knowledge tracking model by investigating the effect of the relationship between practice questions on the prediction results, and then using the attention mechanism and BiGRU neural network [27]. The optimization process starts with modeling the learner using BiGRU neural network, which integrates the learner's past and future contextual sequence information into the model's multiple knowledge point concepts. In addition, the attention mechanism is integrated into the deep knowledge tracking model by assigning initial values to the attention weights, while continuously updating the values of the attention weights as the model is trained, and directly capturing the relationships between the input practice questions through the attention weights.

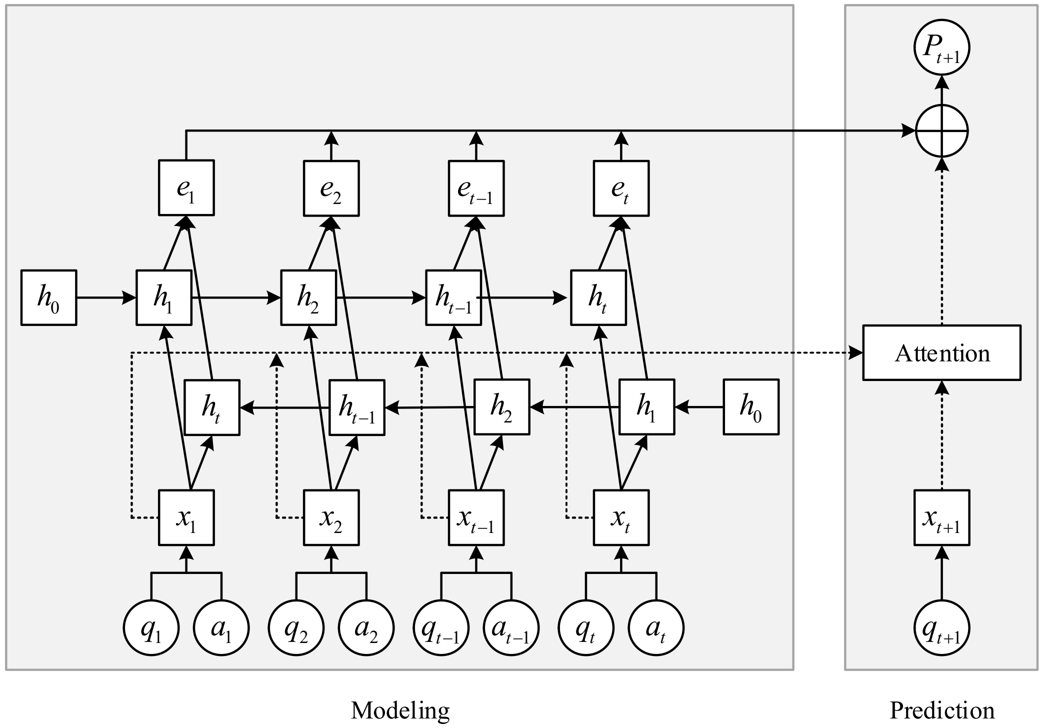

Fig. 2. SA-BiGRU model framework

In this paper, a BiGRU neural network is used to model learners, and the real-valued vectors of each particular learner's practice process are used as input. Assuming that the time step forward hidden state is $\overrightarrow{h_t} \in R^{n\times h}$ (the number of forward hidden units is h) and the reverse hidden state is $\overleftarrow{h_t} \in R^{n\times h}$ (the number of reverse hidden units is h), two GRU neural networks in opposite directions are trained simultaneously, and by connecting the two hidden layers in opposite directions to the same output, the output layer can obtain information about the forward and backward states at the same time. The past and future context sequence information of the learner is integrated into the multiple knowledge point concepts of the model to more accurately simulate the learning state of the learner, thus disregarding the length of the input sequence. The above process can be represented as follows:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{8}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{9}$$

$$\overline{h} = \tanh(W_{\overline{h}} \cdot [r_t * h_{t-1}, x_t]) \tag{10}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \overline{h_t} \tag{11}$$

$$y_t = \sigma(W_0 \cdot h_t) \tag{12}$$

$$h_t = \vec{h}_t \oplus \overleftarrow{h}_t \tag{13}$$

where x_i denotes the input at the current moment, h_{t-1} denotes the output at the previous moment, $W_r, W_z, W_{\overline{h}}, W_0$ are the corresponding weight matrices, z_t and r_t respectively denote update gates and reset gates, [] denotes the concatenation of matrices, and * denotes the multiplication of matrix elements.

3.2.2. Attention module. Relationships between exercises performed by students have an impact on their state of mastery, which is captured using a weighted exponential decay mechanism. The first attention calculation query matrix and key-value pairs are represented as:

$$Q_1 = EW^{n_1}; K_1 = I_G W^{k_1}; V_1 = I_G W^{v_1} \tag{14}$$

Where W^{φ_1}, W^{k_1} and W^{v_1} are parameter matrices, which are used to learn the effect of previously done knowledge points on the current knowledge points. In addition, an exponential decay term is introduced to obtain higher weights at shorter distances [28]. The formula for the attentional weights is as follows:

$$A(Q_1, K_1, V_1) = Softmax\left(\frac{Q_1 K_1^T}{\sqrt{d}} B\right) V_1 \tag{15}$$

For B, an exponential term β^{i-j} is multiplied by an exponential term β^{i-j} on each of the corresponding terms, where $i \geq j, \beta < 1$. The Softmax term is computed specifically as follows:

$$s_i = \frac{q_i^T k_j}{\sqrt{d}} \cdot \beta^{i-j} \tag{16}$$

The above addresses a single attention matrix, and in order to obtain fuller information from the data, this study uses multiple attention matrices, i.e., multiple attention mechanisms. Then:

$$U_1 = c(W_{head_1^1}, \cdots, W_{head_1^k}) W_1^0 \tag{17}$$

where $W_{head_1^i} = A(Q_1^i, K_1^i, V_1^i)$, and c is a matrix splicing operation with the parameter matrices $W_1^0 \in R^{h \times d \times d}; U_1 \in R^{a \times d}$.

In order to better capture the impact of exercises performed by students in the past on the present, this study inputs E_c as Q into the attention mechanism. The 2nd attention computation query matrix and key-value pair formula are as follows:

$$Q_2 = E_G W^{q_2}; K_2 = U_1 W^{k_2}; V_2 = U_1 W^{v_2} \tag{18}$$

Where W^{q_2}, W^{k_2} and W^{v_2} are parameter matrices. The formula for calculating the attention weights is as follows:

$$A(Q_2, K_2, V_2) = Softmax\left(\frac{Q_2 K_2^T}{\sqrt{d}} B\right) V_2 \tag{19}$$

The formula for calculating long attention is as follows:

$$U_2 = c(W_{head_2^1}, \cdots, W_{head_2^h}) W_2^0 \tag{20}$$

where $W_{head_2^i} = A(Q_2^i, K_2^i, V_2^i)$, and parameter matrices $W_2^0 \in R^{k \times d \times d}; U_2 \in R^{n \times d}$. The U_2 processed by the attention mechanism contains the student's mastery of the knowledge concepts, then it will be fed into the next layer of the network structure.

In this study, causal convolution is used for local feature extraction. The output of each layer of causal convolution is jointly obtained from the unknown input of the previous layer and the input of the same position of the previous layer, which achieves local feature extraction by controlling the size of the convolution kernel, and solves the sequential problem that cannot be solved by traditional convolution. The size of the convolution kernel is fixed in a specific range, and only sequences within this range are computed, whereas an output in traditional convolution is computed from the corresponding sense field of the convolution kernel. This computation takes into account the sequential nature of the sequence and agrees with the requirements of the target sequence.

The student knowledge point mastery feature $U_2 \in R^{n \times d}$ is used as the input to this layer. Specifically, the input $U_2^T = (m_1, m_2, \cdots, m_n), m_i \in R^{d \times 1}$ is obtained by convolving $H^c = (h_1^c, h_2^c, \cdots, h_{n+k-1}^c) \in R^{d \times (n+k-1)}$.

Among them:

$$h_i^c = \text{Relu}\left(\sum_{j=1}^{d} G \times (m_{i-k+1}^i, m_{i-k+2}^i, \cdots, m_i^j)^T + b\right) \tag{21}$$

where $G \in R^d \times k$, i.e., d convolutional kernels of length k, m_i^j is the m_i dimension element of m_i, $b \in R^{d\times 1}$ is the function bias term, and ReLU- $\max(0, x)$ is the activation function. For ease of modeling, this study takes the first n dimensions, i.e., the output of this layer is $H^c \in R^{d\times n}$.

3.2.3. Outputs and Optimization Objectives. BiGRU neural network depends on the current input and hidden state at each time step, and there is still a possibility of long sequence problems occurring, while the attention mechanism can adaptively select task-related information according to the current input and the previous hidden state, providing the model with fine information selection. Thus, it alleviates the long sequence problem, compensates for the information loss caused by long dependency, deepens the influence of learners' historical answer performance on future performance, and improves the accuracy of prediction.

Therefore, the prediction output module of SA-BiGRU uses the scaled dot product vector self-attention mechanism to compute the correlation weights of the learners' historical knowledge states, and generates knowledge state vectors with attention weights for predicting learners' future performance. Then:

$$\begin{aligned} m &= Attention(Q, K, V) \\ &= softmax(\frac{QK^T}{\sqrt{d_k}})V \end{aligned} \tag{22}$$

$$\begin{cases} Q = W_q h_t \\ K = W_k h_t \\ V = W_v h_t \end{cases} \tag{23}$$

After passing the learner's knowledge state m with fused attention weights through the sigmoid activation layer, the prediction results of the learner's mastery of all knowledge points can be obtained. Namely:

$$y_t = \sigma(W_y m + b_y) \tag{24}$$

where W_y is the weight matrix.

The training objective of the model is the cross-entropy between the learner's predicted answer performance and the true answer performance at the next moment. Namely:

$$Loss = -\sum a_{t+1} \log(y_t^T \delta(q_{t+1})) - (1 - a_{t+1}) \log(1 - y_t^T \delta(q_{t+1})) \tag{25}$$

where a_{t+1} represents the real answer situation and $\delta(\cdot)$ is the embedded representation of the question.

3.3. Dual College Interdisciplinary Instructional Design

3.3.1. Interdisciplinary teaching objects. Taking a vocational and technical college in Province G as an example, two parallel classes of its mechatronics program were selected as research objects to explore the interdisciplinary knowledge integration between the Civics and Politics curriculum and the mechatronics program. The two classes have a total of 135 students, which are divided into Mechatronics 1 and Mechatronics 2 according to the random sampling method, with 67 and 68 students in each class.

Electromechanical class 1 was chosen as the experimental class, which mainly utilizes the interdisciplinary innovative teaching model established by this paper combined with artificial intelligence technology to carry out interdisciplinary teaching, aiming to enhance students' theoretical and practical knowledge of electromechanics, and also to further improve the level of students' ideological literacy. The electromechanical class 2, as a control class, adopts the traditional electromechanical teaching and ideological teaching mode, each teaching the relevant courses. Through the interdisciplinary knowledge integration teaching of the two classes, as a way to verify the feasibility of AI technology in the interdisciplinary knowledge integration as well as innovative teaching system in dual colleges and universities.

This teaching experiment starts from September 2023 to January 2024, a total of 20 weeks, and the teachers and teaching materials of the two classes are controlled to be the same, so as to better ensure the scientific nature of teaching.

3.3.2. Interdisciplinary Teaching Process. The teaching of mechatronics specialty in higher vocational colleges is related to the cultivation of operational talents, and the interdisciplinary knowledge fusion teaching mode designed by relying on artificial intelligence technology is aimed at ensuring the practical operation ability of talents on the basis of better enhancing their ideological quality, so that they can provide high-skilled and high-quality talents for the development of the society.

Based on this, this paper relies on the interdisciplinary teaching system designed in the previous article, combines online education and the relevant courses of mechatronics majors, and designs its interdisciplinary teaching process as shown in Figure 3. It mainly contains four processes: project initiation, project implementation, results appreciation and multiple evaluation, which effectively enhances students' ideological awareness, operational ability, social responsibility and innovation ability.

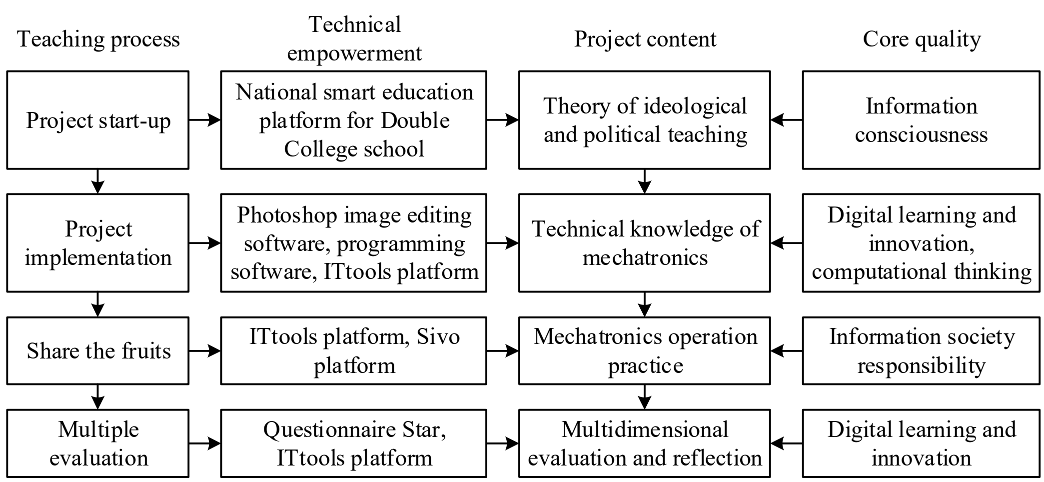

Fig. 3. Interdisciplinary teaching process

4. Interdisciplinary Knowledge Integration and Teaching Practices in Dual Colleges and Universities

With the continuous development of modern science and technology, artificial intelligence is gradually applied in the field of education. Relying on artificial intelligence technology to assist in realizing the interdisciplinary knowledge integration and innovative teaching system of dual colleges and universities, and then clarify the specific interdisciplinary teaching countermeasures and implementation process. In order to improve students' interdisciplinary awareness and ability, the ability to use the knowledge they have learned to solve interdisciplinary problems, and better enhance the quality of the cultivation of high-skilled and high-quality talents in dual colleges and universities.

4.1. *Knowledge Tracking Performance Comparison*

4.1.1. Model comparison experiments. The role of the knowledge tracking model is to analyze the learners' mastery of knowledge points and state evolution in the process of interdisciplinary knowledge integration teaching, and to assist teachers to better optimize interdisciplinary knowledge integration teaching strategies. In order to verify the performance of the SA-BiGRU model proposed in this paper in interdisciplinary knowledge tracking, eight baseline models, DKT, DKVMN, GKT, DKT-For, SAKT, SKT, HawkesKT, and CL4KT, are selected to conduct the experiments on two real datasets, ASSIST17 and EdNet. For the validity of the models, this paper mainly chooses AUC, ACC, RMSE and R2 as the evaluation indexes. Table 1 shows the performance comparison results of different models for carrying out interdisciplinary knowledge tracing.

It can be seen through observation and analysis that:

1) Compared with other baseline models, the SA-BiGRU model achieves more excellent results on all datasets and evaluation metrics, indicating that the SA-BiGRU model, which takes into account knowledge interactions and memory forgetting factors, is more attuned to the cognitive process of learners' cross-disciplinary knowledge and better improves the prediction performance.

2) Analyzed from the perspective of modeling knowledge interactions, GKT and SKT, which explicitly utilize knowledge structure and influence propagation, are the two models that perform better in the comparison, and the observed results indicate that knowledge relationships and their interactions do provide rich and effective information for estimating learners' interdisciplinary knowledge status. In addition, the SA-BiGRU model that introduces the attention mechanism performs better than the GKT that only constructs prerequisite relations and the SKT that only constructs directed and undirected relations. It indicates that the introduction of past and future relations between interdisciplinary knowledge enriches the topological information of knowledge structure and can effectively improve the model performance.

3) Analyzing from the perspective of modeling time, the DKT-For and SA-BiGRU models considering forgetting features perform better than the original DKT and GKT models, which verifies the effectiveness of introducing time-related factors in reasonably modeling the evolution of knowledge states.

4) Analyzing from two perspectives, compared with DKT-For and HawkesKT, which only consider forgetting features, and GKT and SKT, which only consider influence propagation among knowledge and ignore forgetting features, the SA-BiGRU model highlights the performance advantages of the SA-BiGRU model by utilizing causal convolution to realize influence propagation of multiple relationships among knowledge and the gating mechanism that integrates temporal information.

5) From the RMSE and R2 of the models, the SA-BiGRU model has the lowest RMSE and the largest R2, which indicates that the SA-BiGRU model has a good scalability on the feature distribution of different datasets.

6) It is observed that the AUC values predicted by all the models for the ASSIST2017 dataset are the lowest among all the datasets due to the fact that this dataset contains a wide variation of learner behaviors, which puts a higher demand on the knowledge tracking task and increases the task difficulty and complexity.

Table 1. Performance comparison results of different models

Model	ASSIST17				EdNet			
	AUC	ACC	RMSE	R2	AUC	ACC	RMSE	R2
DKT	0.658	0.651	0.538	0.304	0.751	0.782	0.418	0.285
DKVMN	0.703	0.678	0.529	0.296	0.816	0.815	0.411	0.271
GKT	0.724	0.692	0.501	0.287	0.824	0.816	0.396	0.269
DKT-For	0.667	0.679	0.514	0.312	0.818	0.815	0.375	0.254

SAKT	0.663	0.641	0.546	0.309	0.789	0.794	0.382	0.263
SKT	0.735	0.694	0.502	0.273	0.824	0.815	0.391	0.261
HawkesKT	0.661	0.663	0.553	0.261	0.763	0.793	0.379	0.226
CL4KT	0.658	0.652	0.558	0.268	0.785	0.796	0.374	0.225
SA-BiGRU	**0.746**	**0.705**	**0.419**	**0.352**	**0.837**	**0.841**	**0.362**	**0.304**

The embedding vector of the knowledge point representation implies the learner's interdisciplinary knowledge state, and the high level of the vector's representation of the learner's interdisciplinary knowledge state can be measured using its consistency with the actual knowledge points (DOA). The consistency formula reflects the level of consistency between the learner's knowledge state predicted by the model and the learner's mastery of actual knowledge points, and the higher the index, the more consistent the model's predicted effect is with the learner's mastery of actual knowledge points. Figure 4 shows the results of the comparison of the quality of knowledge point representations of different models on different datasets.

As can be seen from the figure, the SA-BiGRU model achieved better values for the quality of interdisciplinary knowledge representation on both datasets, 0.828 and 0.845, respectively. This demonstrates the feasibility of the SA-BiGRU model to represent the learners' interdisciplinary knowledge points with an embedding vector in BiGRU model, which can reflect the learners' interdisciplinary knowledge mastery more realistically and accurately. Secondly, the SKT and GKT models performed second only to the SA-BiGRU model, and the reason for analyzing this may be that the SA-BiGRU model introduces the attention mechanism to weight the interdisciplinary knowledge points separately when representing the target knowledge points, and different types of knowledge points are given different weights to represent the target knowledge points more adequately.

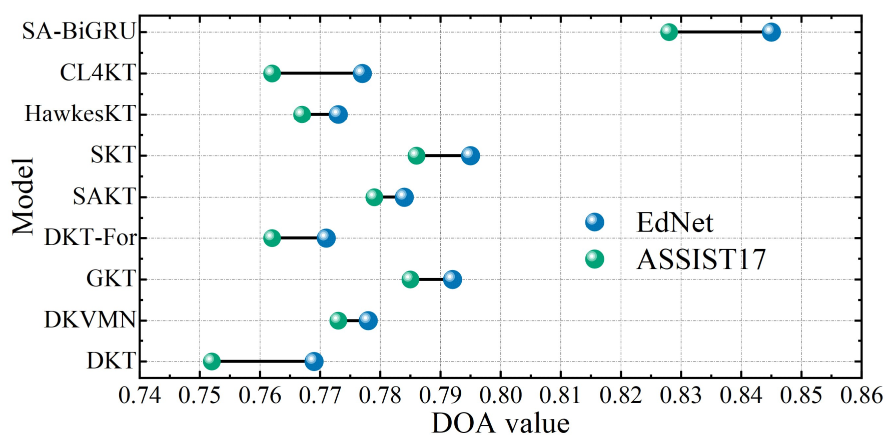

Fig. 4. Knowledge points represent quality comparison results

4.1.2. Model ablation experiments. To further validate the effectiveness of the BiGRU module and the attention module of the SA-BiGRU model, the SA-BiGRU model was compared with three variants of the model. Variant A is the original model with the BiGRU model removed and only the knowledge point tuple data is selected as input. Variant B is the original model with the attention module removed and the weight index decay mechanism deleted. Variant C is the original model with both BiGRU model and attention module removed, and only the LSTM part is retained.The results of the ablation experiments of the SA-BiGRU model on the two datasets are shown in Table 2.

The following conclusions can be drawn from the table:

1) The prediction performance of all three variants of the model declined relative to the original model, which side by side verifies the effectiveness of forgetting behavior modeling and learning ability modeling.

2) Although the prediction performance of variant C is decreased compared with the original model, the prediction performance is higher than that of the DKVMN model, which proves that the improvement of the performance of the DKVMN model by adding the LSTM on the basis of the DKVMN model is effective.
3) The decrease in predictive performance of variant B compared with variant A is more obvious, which indicates that the benefit of predictive performance improvement brought by the attention mechanism is greater than the benefit of predictive performance improvement brought by BiGRU modeling.
4) Compared with the difference in performance between variant B and the original model, the difference in predictive performance of variant C relative to variant A is smaller, and the difference in predictive performance of variant A relative to variant B and variant A relative to the original model is smaller. It indicates that the effect of predictive performance enhancement brought about by the joint action of BiGRU and the attention mechanism is higher than that brought about when they act singly.

Table 2. Results of the ablation experiment of SA-BiGRU model

Model	ASSIST17				EdNet			
	AUC	ACC	RMSE	R2	AUC	ACC	RMSE	R2
A	0.718	0.686	0.482	0.318	0.805	0.782	0.391	0.283
B	0.707	0.678	0.491	0.312	0.783	0.765	0.408	0.268
C	0.651	0.654	0.516	0.295	0.752	0.726	0.415	0.252
DKVMN	0.634	0.627	0.553	0.267	0.738	0.704	0.436	0.215
SA-BiGRU	**0.746**	**0.705**	**0.419**	**0.352**	**0.837**	**0.841**	**0.362**	**0.304**

4.2. Interdisciplinary knowledge visualization

4.2.1. Visualization of knowledge tracing. In order to demonstrate more intuitively the accuracy of the SA-BiGRU model proposed in this paper in portraying students' interdisciplinary knowledge state, this paper takes the selected research subjects as an example, and collects relevant data from their interdisciplinary learning process of conducting mechatronics and civics, and makes a dataset of them. The knowledge interaction record of a student was randomly intercepted from this dataset, and the student's knowledge state was visualized. The visualization of student knowledge status can be achieved by outputting the student's knowledge status after each completion of a specific problem and plotting the student knowledge status in the order of doing the problem as a heat map. The knowledge state visualization can not only be used for personalized instruction of students, but also can verify the actual effect of the knowledge tracking model to a certain extent.

For this student this study selected 18 consecutive questions from the five concepts (Q1~Q5) about mechatronics and Civics teaching content that he/she was exposed to and visualized his/her performance in answering the questions. Figure 5 shows the results of the visualization of the students' interdisciplinary knowledge tracking, where the horizontal coordinate indicates the serial number of the questions, the vertical coordinate indicates the number of the selected concepts, and the likelihood of the learner answering each question correctly is represented by the value of the (0,1) interval, with the color shades used to differentiate between the individual probability values.

As can be seen from the figure, at the beginning of the study, this learner's level of interdisciplinary knowledge is usually low, and his or her mastery of the content related to mechatronics and Civic Education is low. However, with continuous practice, the learner's interdisciplinary knowledge mastery level gradually increases and eventually tends to stabilize. When the learners answered questions 11 and 13, the learners' subsequent knowledge mastery level still showed an upward trend in terms of the overall trend, despite the fact that the answer result at that moment was wrong. This phenomenon can be attributed to the learners' ability to transfer and apply the accumulated interdisciplinary knowledge from the answers to the historical questions to the new ones. It corroborates that modeling the migration representation of interdisciplinary topics considering students' forgetting behavior helps the model to better predict the learners' knowledge mastery status and improve the model accuracy.

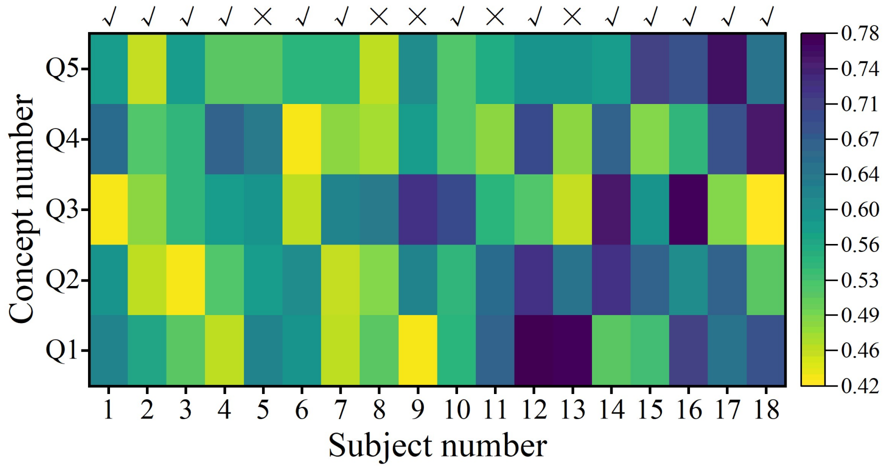

Fig. 5. Interdisciplinary knowledge tracking visual results

In order to more intuitively show the dynamic changes in this learner's mastery of each concept, the data represented in the form of heat map is presented using standard area maps. Figure 6 shows the trend of the learner's interdisciplinary knowledge status, with the horizontal axis representing the time series and the vertical axis corresponding to the learner's knowledge mastery status.

From the figure, it can be seen that the learner's mastery of each concept has a slow growth trend, and it can be found that the prediction of the SA-BiGRU model for the interdisciplinary knowledge mastery state is more in line with the intuition of the general learners' mastery of the concepts, which proves that the prediction of the learner's interdisciplinary knowledge state by the SA-BiGRU model proposed in this paper is reasonable. With these correctness data, dual colleges and universities are able to gain insight into learners' mastery of each concept when teaching interdisciplinary knowledge integration. Based on this analysis, teachers are able to develop a more personalized interdisciplinary knowledge integration instructional plan based on learners' specific learning situations and provide targeted instruction to learners.

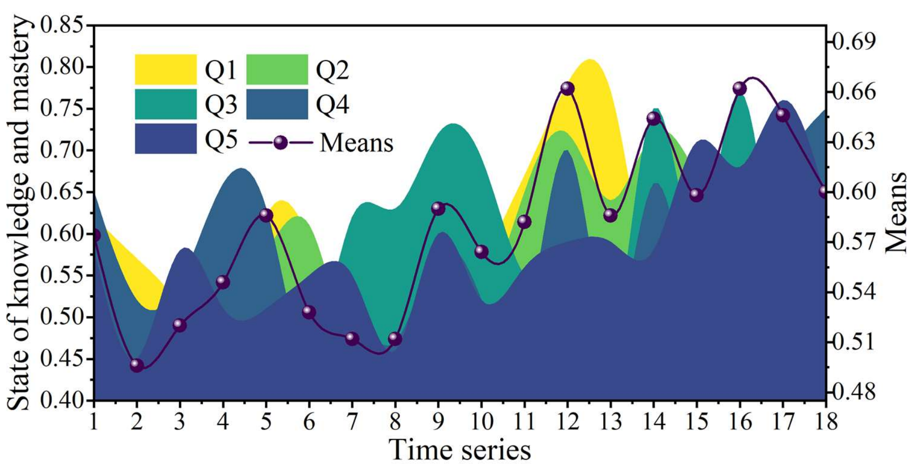

Fig. 6. The trend of interdisciplinary knowledge

4.2.2. Knowledge acquisition. In order to further observe the dynamic changes of students in the interdisciplinary learning process from the initial understanding to the application mastery stage, this section analyzes the preprocessed dataset, divides the students' mastery of interdisciplinary knowledge into three levels, i.e., Levels I-III, and plots the distribution of the students' interdisciplinary knowledge progression states as shown in Figure 7.

It can be found that as the length of the interaction sequence of students' interdisciplinary knowledge learning increases, the distribution of students among the progression states changes gradually. This trend suggests that students' interdisciplinary learning states show differences at different stages and that students' concentration on particular progression states changes as the interdisciplinary learning process advances. For example, in the early stages of interdisciplinary knowledge integration instruction, students may concentrate more on the lower progression state (Level I), while they gradually shift to higher progression states as learning progresses. The division of advancement states effectively reflects students' mastery on different interdisciplinary knowledge points, and higher advancement states usually correspond to higher interdisciplinary knowledge mastery, which also verifies the validity of this paper's model for students' interdisciplinary knowledge tracking task.

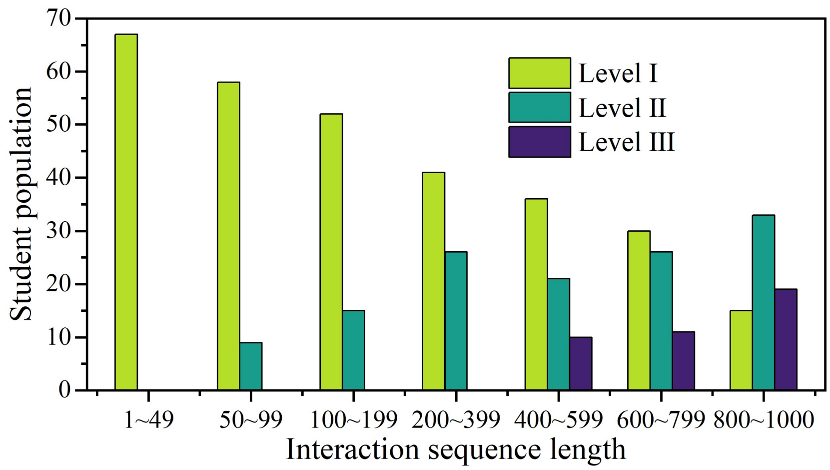

Fig. 7. Interdisciplinary knowledge progressive state distribution

4.3. Validation of interdisciplinary teaching

4.3.1. Interdisciplinary capacity development. The purpose of interdisciplinary knowledge integration in dual colleges and universities is to cultivate more comprehensive, highly skilled and high-quality talents, and to better respond to the needs of society for different types of applied talents. This paper takes students majoring in mechatronics as an example of interdisciplinary integration of Civic and Political Education to enhance the level of students' ideological literacy. For the interdisciplinary innovative teaching system proposed in this paper, this paper carries out a teaching comparison experiment. Before the beginning of the teaching experiment, the interdisciplinary ability of the students in Class 1 and Class 2 was tested, mainly in six dimensions: interdisciplinary knowledge reserve, innovative performance, teamwork, ideological literacy, practical application and overall level.

The questionnaire was quantified using a five-point Likert scale, with 1 to 5 representing very non-compliant, non-compliant, average, compliant and very compliant, respectively. At the end of the teaching experiment, the questionnaire was administered again to obtain the students' interdisciplinary competence development. The data obtained from the two times were organized and entered into SPSS software to carry out independent samples t-test, with $P<0.05$ indicating a statistically significant difference. Table 3 shows the results of independent samples t-test of students' interdisciplinary competence development.

Before the beginning of the teaching experiment, there is no significant difference between the students of electromechanical class 1 and class 2 in terms of interdisciplinary knowledge reserve, innovative performance, teamwork, ideological quality, practical application and overall level (P>0.05), which also indicates that the subjects of the teaching experiment selected in this paper have the same level of interdisciplinary ability, which can reveal the effectiveness of interdisciplinary innovative teaching system empowered by artificial intelligence. At the end of the teaching experiment, the students of E&E class 1 and class 2 showed significant differences (P<0.05) in interdisciplinary knowledge reserves, teamwork, ideological quality, practical application and overall level. Among them, the interdisciplinary knowledge reserve of students in E&E class 1 increased from 2.81±1.47 points before the experiment to 4.17±0.75 points after the experiment, and ideological literacy increased by 1.82 points as a whole, which is a greater change in interdisciplinary competence than that of students in E&E class 2. And there is no significant difference between the teamwork ability of the two classes before and after teaching (P>0.05), and even the teamwork score of E&E 2 class is higher than that of E&E 1 class. This is mainly due to the fact that the interdisciplinary knowledge integration supported by artificial intelligence technology exists partly online teaching, which fails to fully display the practical operation of mechatronics, and the efficiency of teamwork among students is constrained, which is also an important direction for the subsequent optimization of interdisciplinary knowledge integration. In conclusion, the innovative teaching system of interdisciplinary knowledge fusion under artificial intelligence technology support can significantly enhance the interdisciplinary knowledge reserve ability of students, and better enhance the interdisciplinary ability of students.

Table 3. Test results of interdisciplinary ability culture (M±SD)

Dimension	Test	1 Class	2 Class	T	P
Interdisciplinary knowledge reserve	Before	2.81±1.47	2.82±1.36	0.276	0.086
	After	4.17±0.75	2.93±1.52	5.238	0.002
Innovation performance	Before	2.94±0.86	2.91±0.93	0.314	0.095
	After	3.75±0.68	3.08±0.71	2.527	0.027
Term cooperation	Before	2.68±1.13	2.72±1.04	0.553	0.109
	After	3.19±1.35	3.28±1.27	0.349	0.148
Thought literacy	Before	2.46±1.37	2.45±1.42	0.427	0.084
	After	4.28±0.56	2.69±1.21	5.438	0.000
Practical use	Before	2.38±1.25	2.42±1.54	0.276	0.106
	After	4.01±0.84	3.15±0.96	4.219	0.005
Overall level	Before	2.65±1.31	2.56±1.28	0.385	0.127
	After	3.88±0.89	3.13±1.05	3.591	0.038

4.3.2. Satisfaction with interdisciplinary learning. The survey of students' satisfaction with interdisciplinary learning is mainly based on the internal and external environments of students in the process of interdisciplinary learning, and this paper mainly investigates the survey from the three levels of students, teachers and schools. The students' own level is reflected in the lack of perseverance in interdisciplinary learning, while the teachers' level is mainly due to the difficulty in understanding interdisciplinary courses, impractical course contents, lack of attraction in interdisciplinary classrooms, and insufficient attention paid by the teachers to the dual-degree elective courses, and so on. At the university level, it is from the school's support, the rationality of interdisciplinary course arrangement, and interdisciplinary elective opportunities.

The students in E&E 1 class were divided into upper, middle and lower levels according to their rankings, and the results of the variability analysis between the interdisciplinary learning satisfaction of students with different class rankings are shown in Table 4.

As can be seen from the table, the differences in students' total interdisciplinary learning satisfaction scores among students with different class rankings failed to reach a statistically significant difference (F=1.541, P=0.219>0.05). Difference in Interdisciplinary Learning Satisfaction among students with different class rank under student and teacher level failed to reach statistically significant difference with p-values of 0.458 and 0.246 respectively which are greater than 0.05.There is significant difference in the difference in Interdisciplinary Learning Satisfaction among students with different class rank under school level (F=3.127, P=0.021<0.05). The highest total score of learning satisfaction was found in the class rank of upper (19.06±3.48) and the lowest total score of learning satisfaction was found in the class rank of lower (16.79±3.52). The difference in interdisciplinary learning satisfaction between students with class rank of upper and lower showed significant difference (P<0.05). Overall, students with stronger interdisciplinary abilities received the innovative teaching system of interdisciplinary knowledge integration more, while poorer students expressed difficulty in accepting it. In the subsequent optimization process of the innovative teaching system of interdisciplinary knowledge integration, it is necessary to fully consider the satisfaction situation of students under different levels, and reasonably optimize and improve the system according to the needs, so as to help more students to improve their interdisciplinary learning ability, and to lay a solid foundation for the dual colleges and universities to cultivate high-skill and high-quality application-oriented talents.

Table 4. Differential analysis results

	Upper	Medium	Lower	F	P
Total	60.69±8.61	60.47±8.95	55.49±8.76	1.541	0.219
Student	19.48±3.72	19.15±3.75	18.06±3.46	0.624	0.458
Teacher	22.15±4.93	22.08±4.52	20.64±4.87	1.152	0.246
College	19.06±3.48	18.24±3.91	16.79±3.52	3.127	0.021

5. Conclusion

The article proposes an interdisciplinary teaching innovation system based on artificial intelligence technology, establishes the SA-BiGRU model for tracking the change of learners' interdisciplinary knowledge status, and analyzes the effectiveness of the application of the interdisciplinary teaching innovation system through teaching comparison experiments.

1) The AUC and ACC of SA-BiGRU model reached 0.837 and 0.841 on EdNet dataset respectively when tracking interdisciplinary knowledge, which fully demonstrated that SA-BiGRU model could tap learners' interdisciplinary knowledge mastery.

2) At the end of the teaching experiment, the students of E&E class 1 and class 2 showed significant differences (P<0.05) in interdisciplinary knowledge reserve, teamwork, ideological literacy, practical application and overall level. The interdisciplinary knowledge reserve of students in E&E class 1 can be improved by 1.36 points and the level of ideological literacy by 1.82 points compared with that before the experiment.

Supported by artificial intelligence technology, it can better explore the change of learners' knowledge state in the process of interdisciplinary knowledge fusion, provide auxiliary decision-making for teachers to optimize the teaching method of interdisciplinary knowledge fusion, and also provide a new path for dual colleges and universities to cultivate high-skilled and high-quality applied talents.

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