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Research on the Strategy of Building a Civic and Political System for College English Courses by Integrating Q-Learning Algorithm under Blended Teaching Mode

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Abstract Aiming at the main point of the traditional teaching mode in which the language ability cultivation and the Civic and Political education are separated, this study proposes a CD-CAT system for college English based on the blended teaching mode. It constructs a course Civic and Political objective system containing a three-dimensional dynamic objective matrix, and develops a dual-coordinate question bank system integrating linguistic knowledge points and Civic and Political elements. Intelligent algorithms such as Shannon entropy and KL information quantity are introduced to optimize the topic selection strategy, and a dynamic learning path planning model is established by combining Q learning. Under the condition of item parameter U(0.05,0.4), the cognitive model including basic knowledge, basic skills and cognitive process dimensions with a total of 22 attributes is constructed. Student A is selected for application case study. Overall, Student A has a better mastery of basic knowledge and basic skills, with 7 attributes fully mastered, but a poorer mastery of cognitive process attributes, with no attributes fully mastered and more than 50% of attributes in a state of no mastery.

Index Terms curriculum civics, CD-CAT, Q learning algorithm, learning paths

I. Introduction

Nowadays, there are two focuses of attention in the education world, one is curriculum ideology and politics, and the other is mixed teaching. Curriculum Civics and Politics emphasizes the full use of Civics elements in professional education to carry out ideological and political education, deepen students' understanding and mastery of knowledge, and at the same time, strive to improve students' ideological awareness, cultural self-confidence and firm political beliefs [1], [2]. College English is an important carrier for the practice of curriculum ideology and politics, and it is of positive significance to explore the focus point of college English teaching reform under the perspective of curriculum ideology and politics, and explore the integration of curriculum ideology and politics into college English teaching strategies and methods, in order to optimize the effect of college English teaching, give full play to the function of college English in nurturing people, and implement the task of educating people with moral integrity [3]-[6]. And hybrid teaching is now a new teaching mode, which can not only enhance students' learning efficiency and independent learning ability, enrich the effect of English classroom, fill the loopholes of traditional teaching, but also allow students to have more opportunities for independent exploration and cooperative communication in the classroom [7]-[10]. It combines the advantages of traditional classroom and distance education, which not only conforms to the development of the new era, but also cultivates excellent talents according to the needs of the society [11], [12]. Therefore, under the hybrid teaching mode, college English teachers should consider both the teaching of professional knowledge and the ideology of the curriculum, integrate the two organically, so that English majors can realize the comprehensive improvement of knowledge, ability, quality and other aspects [13], [14]. At the same time, due to the introduction of algorithmic technology can empower the high-speed development of the blended teaching of college English course Civics and Politics, through the rapid processing of a large amount of information data, combined with its own push mechanism, empowerment mechanism and embedding mechanism to influence the teaching, which both plays a positive role and presents a certain degree of negative impacts, which is worthy of in-depth study [15]-[17].

This paper firstly discusses the objectives of foreign language courses' Civics and Politics under the hybrid teaching mode, and builds CD-CAT question bank under the guidance of the objective system. Randomized method is used for initial question selection, and diversified question selection strategies are proposed. Use Q-learning algorithm to construct an efficient learning path and realize real-time monitoring of learners' status. Explore the quiz effects of different question selection strategies under different item parameter settings, and determine the item parameter level with the best performance. Construct cognitive attributes from the perspective of the core qualities of ideology and politics, and select 3,688 students as the assessment subjects to carry out experiments. CD-CAT is used as an analytical method to diagnose and analyze students' college English performance.

II. A Cognitive Diagnostic Test of College English Integrating Q-Learning in a Blended Learning Mode

II. A. Objectives of Course Civics in the Hybrid Teaching Model

The hybrid teaching mode has changed the teaching mode, combining traditional offline teaching with online learning, and teachers can use various learning platforms and digital teaching resources to carry out teaching activities, making teaching more flexible, personalized and interactive, improving the teaching efficiency, expanding the way of learning knowledge, facilitating students' thinking and tapping into the elements of Civics, and carrying out Civics education in a subtle way. The ultimate goal of foreign language courses is to cultivate foreign language talents with both cultural background and cultural self-confidence, as well as a sense of mission to disseminate culture to the outside world. In the classroom of comprehensive English courses, teachers should focus on establishing moral values, combine the characteristics of foreign language disciplines, make full use of both online and offline channels, incorporate the elements of Civics and Politics into the traditional teaching of language knowledge, guide the students to establish correct values, enhance the sense of national responsibility of the students, and make the students firm in their cultural self-confidence and patriotic feelings, so that they will ultimately realize the goal of cultivating foreign language talents with both moral and political competence.

II. B. Computerized Adaptive Test Design for Cognitive Diagnosis

The Cognitive Diagnostic Computerized Adaptive Test (CD-CAT) is a test format that combines the strengths of CAT and CD. CD-CAT provides students with a “tailor-made” selection of test questions, which not only provides information on students' mastery of individual knowledge points, but also allows for greater test efficiency. The CD-CAT provides students with a more efficient way to test their knowledge by selecting questions in a “tailored” manner. The selection method is an important part of the CD-CAT, which determines which questions will be selected for students to answer from the question pool. A good selection method enables the CD-CAT to quickly and accurately estimate students' knowledge status, i.e., students' mastery of the knowledge points examined in the test.

II. B. 1) Question bank construction

The question bank is one of the key components of a computerized adaptive test for cognitive diagnosis. The better the quality of the question bank, the more comprehensive the knowledge contained, and the better the test. A good question bank must contain a large number of calibrated, correct questions on each knowledge structure to meet the needs of the actual test. A high-quality question bank is not only about a large number of questions, but also about the cognitive attributes and knowledge systems that are needed for the actual test. In addition to the estimated item parameters, it is important to specify the attributes of the items in the question bank, i.e., the test Q-matrix of the question bank; and for the non-compensatory cognitive diagnostic model with 0-1 scoring, the test Q-matrix should be an adequate test Q-matrix, i.e., the test Q-matrix must include all the columns of the reachable matrix corresponding to the item classes.

Under the guidance of the target system, for the limitation that traditional CD-CAT only focuses on language proficiency but ignores the Civic and Political immersion, this paper spatially associates the language knowledge points with the Civic and Political elements to form a dual coordinate system of knowledge nodes and Civic and Political labels.

II. B. 2) Initial question selection

The traditional method for the selection of initial questions is the randomized method. The randomized method is simple to operate and easy to understand, so the selection of initial questions in this paper uses the most traditional randomized method.

II. B. 3) Strategies for selecting topics

(1) SHE selection strategy

The Shannon entropy (SHE) selection strategy is a method used to measure the uncertainty of a random variable. The smaller the value of Shannon entropy is when the probability distribution is more concentrated at a certain point. The Shannon entropy of the remaining questions in the question bank is calculated based on the estimated value of the subject's knowledge state, and the question with the smallest Shannon entropy value is selected for the subject each time.

The question with the smallest value is selected for the test. In CD-CAT, for each topic, the Shannon entropy is calculated based on the posterior probability of the knowledge state:

$$SHE_j = \sum_{y=0}^{1}\left[\sum_{c=1}^{2^K}\left(\pi\left(\alpha_c \mid x^{(t)}, x_j = y\right)\log\frac{1}{\pi\left(\alpha_c \mid x^{(t)}, x_j = y\right)}\right)\sum_{c=1}^{2^K} p\left(x_j = y \mid x^{(t)}\right)\right] \tag{1}$$

(2) KL informative topic selection strategy

The KL selection strategy (KL) measures the degree of difference between the current subject's estimated attribute mastery pattern and the true attribute mastery pattern. For item j, the KL informativeness is equal to the sum of the KL distances between the current subject's estimated and true attribute mastery patterns.The KL distances are calculated as follows:

$$KL_j\left(\hat{\alpha}_i\right) = \sum_{c=1}^{2^K}\left[\sum_{y=0}^{1} p\left(x_j = y \mid \hat{\alpha}_i\right)\log\left(\frac{p\left(x_j = y \mid \hat{\alpha}_i\right)}{p\left(x_j = y \mid \alpha_c\right)}\right)\right] \tag{2}$$

where $p\left(x_j = y \mid \hat{\alpha}_i\right)$ denotes the probability that the current subject's estimated attribute mastery pattern is $\hat{\alpha}_i$ when the answering response on item j is y. Correspondingly, $p(x_j = y \mid \alpha_c)$ denotes the probability that the subject's true attribute mastery pattern is α_c with an answer response of y on item j.

(3) PWKL question selection strategy

The a posteriori weighted KL informative question selection strategy (PWKL) is an improvement on the KL question selection strategy, where the a posteriori probabilities of attribute mastery patterns are weighted and summed as the weights of the KL distances in order to reflect the different importance of different attribute mastery patterns.

$$\pi\left(\alpha_c \mid x^{(t)}\right) = \frac{p\left(\alpha_c\right)L\left(\alpha_c \mid x^{(t)}\right)}{\sum_{q=1}^{2^K} p\left(\alpha_q\right)L\left(\alpha_q \mid x^{(t)}\right)} \tag{3}$$

$$PWKL_j\left(\hat{\alpha}_i\right) = \sum_{c=1}^{2^K}\sum_{y=0}^{1} p\left(x_{ij} = y \mid \hat{\alpha}\right) \log\left(\frac{p\left(x_{ij} = y \mid \hat{\alpha}_i\right)}{p\left(x_{ij} = y \mid \alpha_c\right)}\right)\pi\left(\alpha_c \mid x^{(t)}\right) \tag{4}$$

where $\pi(\alpha_c \mid x^{(t)})$ is the posterior probability when the subject's knowledge state is α_c.

(4) MPWKL topic selection strategy

In PWKL, the point estimate of the subject's cognitive schema serves as a good summary of the posterior probability distribution. However, in a relatively short test, such point estimates cannot fully demonstrate their value. Therefore, the MPWKL question selection strategy is proposed, which considers all posterior distributions including 2^K kinds of attribute vectors with the following formula:

$$MPWKL = \sum_{d=1}^{2^K}\sum_{c=1}^{2^K}\sum_{y=0}^{1}\log\frac{p\left(x_j = y \mid \alpha_d\right)}{p\left(x_j = y \mid \alpha_c\right)} \tag{5}$$

$$p\left(X_j = y \mid \alpha_d\right)\pi_t\left(\alpha_c \mid x^{(t)}\right)\pi_t\left(\alpha_d \mid x^{(t)}\right) \tag{6}$$

KL, PWKL, and MPWKL question selection strategies select the item with the largest indicator value in the question pool as the next question for the subject to answer. Compared to PWKL, MPWKL is more complex to calculate but has higher measurement accuracy in short tests.

(5) GDI question selection strategy

The GDINA discrimination index (GDI) is a method based on the GDINA model, in which the weighted variance of the probability of success of all possible attribute mastery patterns is evaluated to calculate the discriminative ability of an item, and is used as an indicator of the item's selection. The purpose of the GDI selection strategy is to select more discriminative items for the subjects to answer, and through the use of the GDI selection strategy, it is possible to accurately evaluate the knowledge status of each subject and to design a suitable test for the subjects. By using the GDI question selection strategy, it is possible to accurately assess each subject's knowledge status and design questions that are appropriate to his or her level, thus providing a better understanding of the subject's knowledge level and improving the accuracy of the measurement results. The GDI of topic j is defined as:

$$\varsigma_j^2 = \sum_{l=1}^{2^{K_j^*}} \pi\left(\alpha_{lj}^* \mid x^{(t)}\right)\left(P\left(x_j = 1 \mid \alpha_{lj}^*\right) - \bar{P}_j\right)^2 \tag{7}$$

$$\bar{P}_j = \sum_{l=1}^{2^{K_j^*}} \pi\left(\alpha_{lj}^* \mid x^{(t)}\right) P\left(x_j = 1 \mid \alpha_{lj}^*\right) \tag{8}$$

where $\pi\left(\alpha_{lj}^* \mid x^{(t)}\right)$ represents the posterior probability of the knowledge state α_{lj}^* after answering the first t question, $P\left(x_j = 1 \mid \alpha_{lj}^*\right)$ represents the conditional probability of the knowledge state α_{lj}^* correctly answering the question j, and $\bar{P}_j$ represents the conditional probability of answering the first t question, The average probability of answering the question j correctly for each state of knowledge.

II. C.Learning paths based on Q-learning

Based on the synergy of the first two parts, this part uses the learning algorithm of reinforcement learning for constructing a dynamic adaptive system. Through Markov decision process modeling, the diagnostic data output from CD-CAT is transformed into state transfer probabilities to achieve real-time monitoring of the learner's state.

Reinforcement learning is different from machine learning in that it is model-free, so it does not require a specific model for learning, but rather the agent interacts with the environment (here, the learning system) continuously, and in the process of interaction, the system will construct a state space table to record the agent's “trial and error” process. The learning path planning is shown in Figure 1. Learning path planning is shown in Figure 1, the only actions that can be selected by the agent during the exploration and learning process are up, down, left and right. When the agent chooses the action a, the environment (system) will give a reward value r, then the state space table will be updated. When the reward value is positive, agent will choose action a with high probability next time, and vice versa when the reward value received is negative, it will choose action a with reduced probability, and the cycle is known to repeat until agent reaches the end position.

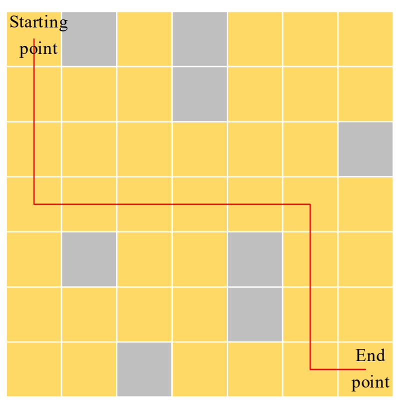


Figure 1: Learning path planning

Since reinforcement learning, unlike deep learning, does not require large amounts of data and labels, it saves a lot of labor and effort. Next, the learning path is modeled based on Markov decision process. All cognitive attributes $\{\alpha\}$ are defined as state space, all learning materials $\mathrm{L} = \{l_1, \cdots, l_L\}$ are defined as behavioral space, and the reward function is shown in the following program:

Because both the state space and the behavior space are discrete states in the algorithm, the classical algorithm in reinforcement learning can be used: the Q learning algorithm. The Q learning algorithm uses the Q function to estimate the behavioral values, denoted by $Q(\alpha, l)$, and the reward values in the algorithm are converted to the current step size. If the learning rate is chosen correctly and the state and behavior space is explored repeatedly, then the Q learning algorithm will converge with probability 1. However, in practice, it generally starts off exploring with ò probability and then continuously decays.

The learning path of the course "College English" constructed by using the Q learning algorithm, the detailed learning path of the queue is shown in Figure 2. The learning path of queue can be followed as given in Fig. 2, after learning the basic concepts of queue first, learning the basic concepts and operations of sequential queue, chained queue and cyclic queue respectively, and finally learning the applications of queue such as recursive and non-recursive implementations, application of queue in hierarchical traversal time and so on.

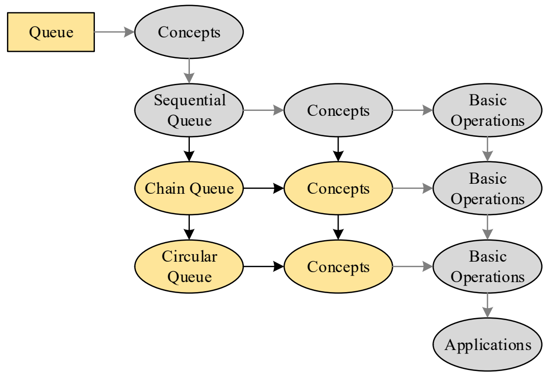


Figure 2: Queue detailed learning path

III. Cognitive Diagnostic Test Construction Based on the Civic System of University English Course

III. A. Selection of project parameters

This section focuses on the test effects of different selection strategies of CD-CAT method under different item parameter settings, in which various condition settings include: two kinds of question bank volume, five kinds of selection strategy indicators, four kinds of attribute numbers, and two kinds of correlation coefficients, and five kinds of selection strategy indicators are selected as SHE, KL, PWKL, MPWKL, and GDI, respectively, and the attribute number of items examined 1, 2, 3, and 4 are respectively are recorded as 1A, 2A, 3A, 4A, i.e., the items are categorized and counted according to the number of attributes examined. In this paper, we focus on analyzing the results under the condition of U(0.2,0.2), which can be regarded as the case when the item parameters are unknown before the question bank is built, and the items are directly set to be equal. The mean values of the number of items at each attribute level for different selection strategies under the conditions of question bank volume 40 and 80 are shown in Tables 1 and 2.

Table 1: Item number distribution when the item bank size is 40

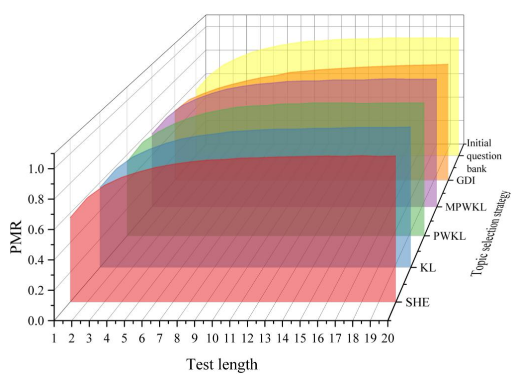
Correlation coefficient	Method	1A	2A	3A	4A
0	SHE	8.9	21.6	7.1	2.4
	KL	40.0	0.0	0.0	0.0
	PWKL	13.7	17.2	6.2	3.0
	MPWKL	15.6	17.3	7.1	0.0
	GDI	23.2	7.7	5.8	3.3
0.5	SHE	8.9	14.9	14.8	1.4
	KL	40.0	0.0	0.0	0.0
	PWKL	12.5	16.6	6.8	4.1
	MPWKL	15.6	17.3	7.1	0.0
	GDI	21.4	8.7	6.1	3.8

From the data in the two tables, it can be seen that when considering the effect of the correlation coefficient alone, as the correlation coefficient increases, (1) there is a decreasing trend in the number of 1A items in the question bank of the GDI selection strategy, while there is an increasing trend in the number of 2A, 3A, and 4A items; (2) there is a decreasing trend in the number of 1A, 2A items, while there is an increasing trend in the number of 3A, and 4A items in the question banks of the PWKL selection strategy; (3) there is a decreasing trend in the number of 2A and 4A items in the question banks of the SHE selection strategy; (4) there is a decreasing trend in the number of 2A and 4A items in the question banks of the KL and MPWKL selection strategies; and (3) The number of 2A and 4A items in the question bank of the SHE selection strategy shows a decreasing trend, while the number of 3A items shows an increasing trend; (4) The question banks of the KL and MPWKL selection strategies do not show any trend when the question bank is small, but the number of 1A items in the KL selection strategy is much higher than that in the other six methods because the setting of the item parameter has a certain effect. When the item parameters are all equal, the KL selection strategy prioritizes single-attribute questions by default, and only when the single-attribute questions are all selected will other attribute questions be selected. Since the question pool of the KL selection strategy contains more single-attribute questions, the accuracy rate is also higher.

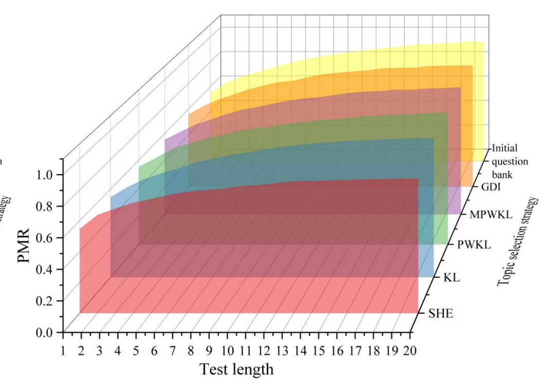
Table 2: Item number distribution when the item bank size is 80

Correlation coefficient	Method	1A	2A	3A	4A
0	SHE	25.1	37.2	13.3	4.4
	KL	78.2	1.8	0.0	0.0
	PWKL	22.7	37.8	14.7	4.8
	MPWKL	37.7	37.7	4.6	0.0
	GDI	52.7	11.9	12.4	3.0
0.5	SHE	24.8	36.1	15.2	3.9
	KL	76.5	3.5	0.0	0.0
	PWKL	21.7	34.7	15.2	8.4
	MPWKL	34.8	34.8	10.4	0.0
	GDI	40.7	19.2	15.7	4.4

From the data in the two tables, it can be seen that when considering the effect of the correlation coefficient alone, as the correlation coefficient increases, (1) there is a decreasing trend in the number of 1A items in the question bank of the GDI selection strategy, while there is an increasing trend in the number of 2A, 3A, and 4A items; (2) there is a decreasing trend in the number of 1A, 2A items, while there is an increasing trend in the number of 3A, and 4A items in the question banks of the PWKL selection strategy; (3) there is a decreasing trend in the number of 2A and 4A items in the question banks of the SHE selection strategy; (4) there is a decreasing trend in the number of 2A and 4A items in the question banks of the KL and MPWKL selection strategies; and (3) The number of 2A and 4A items in the question bank of the SHE selection strategy shows a decreasing trend, while the number of 3A items shows an increasing trend; (4) The question banks of the KL and MPWKL selection strategies do not show any trend when the question bank is small, but the number of 1A items in the KL selection strategy is much higher than that in the other six methods because the setting of the item parameter has a certain effect. When the item parameters are all equal, the KL selection strategy prioritizes single-attribute questions by default, and only when the single-attribute questions are all selected will other attribute questions be selected. Since the question pool of the KL selection strategy contains more single-attribute questions, the accuracy rate is also higher.



(a) U (0.05,0.4)



(b) U (0.2,0.2)

Figure 3: Comparison of the accuracy of the two item parameters

Next, the effect of item parameters on the accuracy rate is analyzed. A comparison of the mean values of the pattern's adjudication rates for the initial question pool, and the 5 question selection strategies under the 2 item parameter conditions is shown in Fig. 3(a-b). From Figure 3, it can be seen that (1) under the 2 item parameters, the mean pattern judgment rates under all 6 question banks increase with the increase of test length; (2) the difference in the judgment rates under the 6 question banks increases with the increase of test length; and (3) under the item parameter U (0.05,0.4), the judgment rates of the question banks under the question selection strategies of SHE, KL, PWKL, and MPWKL are all better than those of the question banks under the GDI The item selection strategies had higher and infinitely closer to the initial question bank judgment rates; while under item parameter U (0.2,0.2), the question bank judgment rates of KL, MPWKL, and PWKL selection strategies were nearly the same as those of the GDI selection strategy; and the SHE selection strategy had the lowest question bank judgment rates because SHE took into account the experiential distributional information of the subject's knowledge state.

In summary, the experiment at the item parameter level of U(0.05,0.4) better reflects the performance variability of the six methods and has a higher accuracy rate.

III. B. Construction of Cognitive Attributes

From the perspective of Civic and Political Science Core Literacy, the key competencies and essential qualities included in Core Literacy are a high degree of generalization and refinement and integration of the three-dimensional objectives, and a transcendence on the basis of inheritance, in which the knowledge and skills, processes and methods of the three-dimensional objectives correspond to the key competencies of the core literacy, and the emotions, attitudes, and values of the three-dimensional objectives correspond to the key qualities of the core literacy. However, knowledge, skills and processes can be portrayed by attributes in cognitive diagnostic assessments and are highly measurable, while students' affective attitudes and values are often difficult to measure with simple tests. In the study of college English core competence, based on this idea, this paper will analyze three dimensions of basic knowledge, basic skills and cognitive process in order to analyze students' college English learning more comprehensively. Eight cognitive attributes are formed in the dimension of basic knowledge, seven cognitive attributes in the dimension of basic skills and seven cognitive attributes in the dimension of cognitive process.

III. C. Application of cognitive diagnostics

In the selection of research subjects, the representativeness of the sample was taken into account as much as possible, and five cities were selected as test areas in this paper. In the selection of each area, we also try to combine urban and rural schools, and match high-quality schools with ordinary schools. A total of 16 schools with 3,688 students were selected as the test subjects. The CET-4, a mature international large-scale test, was selected as the test item, and was modified on the basis of the CET-4 test, i.e., the existing traditional test was processed to form a diagnostic analysis tool with cognitive diagnostic function.

Learning path is a cognitive roadmap constructed based on the containment relationship between each student's knowledge states, and this roadmap provides help for students' personalized learning arrangement. However, in addition to this, we are concerned with the cognitive sequence of each student's learning, but also with the progression constituted by the group of students, i.e., the students' learning progression. Based on cognitive diagnosis and item response theory, this section examines the learning progression of the different dimensions of students' attribute development in terms of the competencies corresponding to their knowledge states.

III. C. 1) Learning progression in the basics dimension

The basic assumption of the construct of learning path is that the acquisition of student knowledge or skills is gradual, i.e., the acquisition of knowledge is sequential. That is, the knowledge state of mastering an attribute (00000000) is labeled as layer 0, the knowledge state of mastering an attribute (00000001) and (00001000) are labeled as layer 1, and so on to form a total of 9 layers from 0 to 8. The calculated ability value corresponding to the knowledge state is shown in Table 3. From Table 3, it can be seen that the knowledge state (00000000) that has not mastered any attributes corresponds to the smallest competence value of -1.55, and the knowledge state (11111111) that has mastered all attributes corresponds to the largest competence value of 0.59. In order to construct the learning progression, these knowledge state competency values were divided and five levels of learning progression were constructed. According to the corresponding knowledge states in different ability intervals, the learning progression corresponding to that interval can be abstracted, thus defining the 5 levels of learning progression for the basic knowledge dimension.

Table 3: Ability value corresponding to knowledge state of basic knowledge dimension

Knowledge state	Ability value	Variance	Knowledge state	Ability value	Variance	Knowledge state	Ability value	Variance
00000000	-1.55	0.22	00010011	-0.58	0.03	10010111	-0.25	0.01
00000001	-1.28	0.11	10010001	-0.52	0.01	00111111	-0.18	0.05
00010000	-1.06	0.08	00100111	-0.49	0.05	10011111	-0.21	0.02
00100001	-1.03	0.03	10000111	-0.45	0.06	01011111	-0.17	0.06
10000001	-0.94	0.01	00010111	-0.37	0.02	01011111	-0.12	0.03
00010010	-0.58	0.05	10010011	-0.42	0.09	10111111	-0.09	0.04
10010000	-0.63	0.12	00101111	-0.29	0.03	11011111	-0.01	0.13
00100011	-0.59	0.04	10001111	-0.26	0.11	01111111	0.15	0.09
10000011	-0.64	0.02	00011111	-0.28	0.05	11111111	0.59	0.25

III. C. 2) Learning progression in the basic skills dimension

Using the cognitive diagnostic model, the knowledge status of each student in the basic skills dimension is obtained using the Q matrix generated from the basic skills attributes, and then the knowledge status is summarized to obtain the learning path in the basic skills dimension. The competence values corresponding to different knowledge state classes were calculated, and the results of competence value calculation are shown in Table 4. Table 4 shows that the knowledge state (0000000) corresponds to the smallest competence value, with a value of -1.71, and the knowledge state (1111111) corresponds to the largest competence value, with a value of 0.62. Therefore, it is divided into five tiers according to the competence value, and the attributes corresponding to the knowledge states that fall in different competence intervals are extracted to constitute the definition of learning progression.

Table 4: Ability values corresponding to knowledge state of basic skill dimension

Knowledge state	Ability value	Variance	Knowledge state	Ability value	Variance	Knowledge state	Ability value	Variance
0000000	-1.71	0.23	0000111	-0.64	0.04	1101101	-0.18	0.02
0001000	-0.98	0.12	1100001	-0.65	0.03	1111011	-0.13	0.03
0000100	-0.92	0.09	1101001	-0.41	0.03	1110111	-0.12	0.01
1000000	-1.03	0.07	1000111	-0.46	0.02	1101111	-0.05	0.01
0001001	-0.82	0.08	1101001	-0.39	0.03	1111101	-0.11	0.03
0000101	-0.79	0.06	1111001	-0.25	0.01	1111111	0.62	0.21
1100000	-0.77	0.08	1100111	-0.22	0.01	\	\	\
1001001	-0.68	0.05	1101011	-0.21	0.02	\	\	\

III. C. 3) Learning progression in the cognitive process dimension

The construction method of cognitive process learning progression is consistent with that of basic knowledge dimension and basic skill dimension, and the competence values corresponding to different knowledge state classes are calculated, and the results of competence value calculation are shown in Table 5. Table 5 shows that the knowledge state (0000000) corresponds to the smallest competence value, with a value of -1.48, and the knowledge state (1111111) corresponds to the largest competence value, with a value of 0.62. Therefore, in accordance with the same methodology of the learning progression construction for the basic knowledge and basic skill dimensions, the attributes corresponding to the knowledge states that fall into different competence intervals are extracted to form the definition of the learning progression.

Table 5: Ability values corresponding to knowledge state of cognitive dimension

Knowledge state	Ability value	Variance	Knowledge state	Ability value	Variance	Knowledge state	Ability value	Variance
0000000	-1.48	0.25	0100011	-0.71	0.04	0110111	-0.35	0.03
0000010	-1.02	0.11	0110001	-0.73	0.04	1001111	-0.29	0.00
0010000	-0.95	0.09	1001001	-0.69	0.02	1110111	-0.22	0.02
0001000	-0.93	0.08	1100011	-0.61	0.04	0111111	-0.17	0.01
0100010	-0.82	0.06	0110011	-0.57	0.03	1011111	-0.19	0.03
0110000	-0.88	0.07	1001101	-0.53	0.01	1101111	-0.16	0.01
1001000	-0.79	0.05	1100111	-0.42	0.02	1111111	0.62	0.23

III. C. 4) Diagnostic case studies

Cognitive diagnostic assessment can obtain each individual's fine-grained attribute mastery information, and this information can be formulated into a personalized diagnostic report after simple aggregation and processing. In this section, a student was randomly selected for the case study, and in order to get more detailed diagnostic information about Student A more intuitively, the mastery degree of each attribute of the student's basic knowledge dimension, basic skills dimension, and cognitive process dimension was aggregated, and Student A's s diagnostic information card is shown in Figure 4.

As can be seen from Figure 4, in the cognitive process, the student has fully mastered the three attributes of "vocabulary breadth", "rhetorical application" and "grammatical reserve". Therefore, the content involving these attributes can be left unscheduled for the short term. Although the attributes of "grammatically accurate" and "coherent text" show that they have mastered the basics, the mastery is not high enough, and some reinforcement learning is needed to strengthen the consolidation. The attributes of "concept mastery", "sentence pattern application" and "grammar mastery" are not mastered, and they need to be rearranged and systematically learned, and some basic training should be carried out. In the dimension of basic skills, the student has fully mastered the four attributes of "oral expression", "writing ability", "translation ability" and "matching ability", but has not mastered the attributes of "listening and decoding", "reading ability" and "application skills". In the dimension of cognitive process, the student did not fully grasp any attributes, basically mastered the attributes of "reasoning and judgment" and "drawing inferences", and partially mastered the attributes of "information extraction", while the four attributes of "critical thinking", "transfer application", "cognitive monitoring" and "self-assessment" were not mastered, and further learning was needed to improve the cognitive process of the corresponding attributes.

Overall, Student A has a better grasp of the basics and basic skills, with more attributes fully mastered, but in the cognitive process attributes, the grasp is poorer, with no attributes fully mastered and more than half of the attributes are in a state of no mastery, so this student needs to pay special attention to the cognitive process aspect of the improvement in their learning.

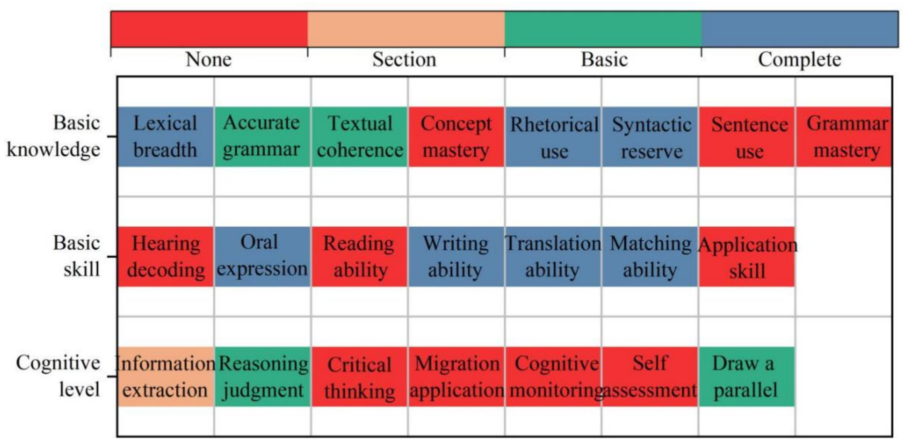


Figure 4: Diagnostic information card of student A

IV. Conclusion

Based on the blended teaching mode, this paper builds a cognitive diagnostic test system for college English integrating Q-learning from the perspective of core ideological and political literacy.

Under the item parameter level of U (0.05,0.4), which better reflects the performance differences of the six methods and has a high accuracy rate, eight cognitive attributes are formed in the basic knowledge dimension, seven cognitive attributes in the basic skills dimension, and seven cognitive attributes in the cognitive process dimension.

In the basic knowledge dimension, the knowledge state (00000000) that has not mastered any attribute corresponds to a minimum of -1.55 competence value, and the knowledge state (11111111) that has mastered all attributes corresponds to a maximum of 0.59 competence value. For the basic skills dimension, the knowledge state (000000000) corresponds to the smallest competence value with a value of -1.71 and the knowledge state (11111111) corresponds to the largest competence value of 0.62. For the cognitive process dimension, the knowledge state (000000000) corresponds to the smallest competence value with a value of -1.48 and the knowledge state (11111111) corresponds to the largest competence value of 0.62. Student A was selected for the application case study. Overall, Student A had a better mastery of basic knowledge and basic skills, with seven attributes fully mastered, but a poorer mastery of cognitive process attributes, with no attributes fully mastered and more than 50% of the attributes in a state of no mastery.

The Cognitive Diagnostic Assessment uses the attributes of student learning as the basic diagnostic unit to diagnose student achievement and learning at a fine-grained level from multiple dimensions of a given subject, enabling a better understanding of the state of student knowledge.

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References

[1] Zhang, Y. (2025). Research on Innovative Approaches to Ideological and Political Education of Foreign Language Majors Based on Projects. Journal of Education, Humanities, and Social Research, 2(1), 34-37.
[2] Li, F., & Fu, H. (2020). Study on college English teaching based on the concept of ideological and political education in all courses. Creative Education, 11(7), 997-1007.
[3] Xie, Q. (2025). Research on Ideological and Political Education in College English Curriculum Under the Reading Circle Teaching Model in Application-Oriented Universities. International Educational Research, 8(1), p42-p42.
[4] Luo, X. (2025). Exploration of Curriculum-based Ideological and Political Education Elements in Academic English Teaching—Taking the Textbook Academic English (An Integrated Course) as an Example. The Educational Review, USA, (12).
[5] Gao, N. (2025). Research on the Countermeasures of Ideological and Political Education in Industry English Courses in Vocational Colleges. New Explorations in Education and Teaching, 2(10).
[6] Zhang, M. (2021). Ideology in college English teaching under the background of courses for ideological and political education. Open Access Library Journal, 8(02), 1.
[7] Zhang, D. (2025). SuperHyperSoft Framework for College English Blended Teaching Quality Evaluation in the New Era: Addressing Uncertainty and Complexity. Neutrosophic Sets and Systems, 80(1), 18.
[8] Liu, L. (2025). Research on the Blended Teaching Model of Translation Courses for English Majors in the Context of New Liberal Arts. Evaluation of Educational Research, 2(7).
[9] Zhang, J., Huang, Y., Wu, F., Kan, W., & Zhu, X. (2025). Scaling up online professional development through institution-initiated blended learning programs in higher education. The Internet and Higher Education, 65, 100988.
[10] Mingxing, G. (2025). Theoretical Design and Practical Application of Core Elements of Blended Teaching Model in the Post-pandemic Era. In Leading Smart Education: Best Practices from Chinese Schools (pp. 171-175). Singapore: Springer Nature Singapore.
[11] Muhiddinovna, F. F. (2025). BLENDED TEACHING: COMBINING TRADITIONAL AND DIGITAL METHODS. Web of Teachers: Inderscience Research, 3(1), 161-162.
[12] Dandan, L. (2022). A study on the application of current affairs in college English blended teaching from the perspective of ideological and political education. International Journal of New Developments in Education, 4(16).
[13] Xuemei, C., Keyuraphan, L., Sethakhajorn, S., & Mingmit, N. (2025). Sustainable Development Strategies to Improve the Effectiveness of College English Hybrid Teaching Literacy of Normal Universities in Sichuan Province. International Journal of Education and Literacy Studies, 13(2), 552-562.
[14] Du, Y. (2023). Study on POA-based integration of ideological and political education into blended teaching of college public English. Sch Int J Linguist Lit, 6(2), 147-151.
[15] Huang, Y., & Yu, J. (2025). An Integrated Plithogenic MCDM Approach College English Blended Teaching Quality Evaluation. Neutrosophic Sets and Systems, 79(1), 35.
[16] Huang, P. (2024). Research on Personalized Ideological and Political Education Content Distribution System Based on Intelligent Algorithms. International Journal of High Speed Electronics and Systems, 2540151.
[17] Wang, Y. (2021). Ideological and political teaching model using fuzzy analytic hierarchy process based on machine learning and artificial intelligence. Journal of Intelligent & Fuzzy Systems, 40(2), 3571-3583.