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Exploring the Path of Deep Learning to Promote the Intelligent Development of Civic and Political Education Theory System in the New Era

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SUMMARY: *Deep learning's strengths in data mining make it highly valuable for intelligent education applications. This paper annotates ideological and political knowledge points with relational labels and designs a visual-language multimodal interaction architecture to perform interactive preprocessing of knowledge point features. We construct a Knowledge Tracking Model (TCKT) based on interactive feature mining, which employs interactive feature embedding and a Learning Behavior Simulation (LBS) module to deeply track students' ideological and political knowledge status and learning proficiency. After annotation, a summary of 30 knowledge points was completed. The TCKT model achieved scores exceeding 90% across all four metrics in knowledge tracking experiments. The TCKT's prediction probability for exercise-concept interactions ranged from 0.61 to 0.69. Deep knowledge tracking achieved an 80.2% interpretability rate for students' systematic learning of ideological and political education.*

KEYWORDS: *Deep learning; Knowledge tracking; TCKT; LBS; Ideological and political education*

1 Introduction

As China advances its socialist modernization drive, educational modernization and the building of an education powerhouse will inevitably enter a new phase of development, with the nation placing ever-higher demands on the quality of talent cultivation. Against the backdrop of the new era, fully leveraging big data, artificial intelligence, and other next-generation information technologies to enhance the intelligence level of the ideological and political education theoretical system holds significant importance for promoting students' all-round development in morality, intelligence, physical fitness, aesthetics, and labor. Fundamentally, ideological and political work is about working with people. It must revolve around students, care for students, and serve students. We must promote the deep integration of the traditional strengths of ideological and political work with information technology to enhance its contemporary relevance and appeal [1]. The intelligent development of student ideological and political education should adhere to a student-centered approach, aim to cultivate high-quality talent, and be driven by innovative technologies like deep learning and artificial intelligence. This will continuously enhance the appeal, persuasiveness, and targeted effectiveness of ideological and political education, vigorously promoting the quality improvement and substantive development of student ideological and political education.

Currently, research in the field of intelligent ideological and political education remains

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limited and is still in its exploratory phase. Existing academic studies primarily focus on the innovative development of ideological and political education empowered by algorithms such as big data and deep learning in the era of artificial intelligence. Reference [2] combines Convolutional Neural Networks (CNN) and Long Short-Term Memory Networks (LSTM) to construct a deep learning model for optimizing the university ideological and political education system. This aims to provide students with personalized learning paths through intelligent algorithms, thereby enhancing effectiveness and student engagement. Reference [3] employs deep learning algorithms and collaborative filtering techniques to develop an enhanced recommendation algorithm for ideological and political education resources. This approach seeks to improve adaptive teaching, strengthen teacher-student interaction, and refine instructional strategies. Reference [4] integrates educational psychology with deep learning algorithms to propose a comprehensive online teaching model for university ideological and political courses. This model addresses the widespread issue of low teaching efficiency in China's higher education institutions, yielding positive outcomes in student comprehension, engagement, and classroom atmosphere. Reference [5] introduced deep learning algorithms into the ideological and political theory system of higher education institutions. It found that students demonstrated strong acceptance of ITCs (Interactive Teaching Content) and achieved significant learning progress, with results providing reference for teaching innovation. Literature [6] employs deep learning to analyze interactive patterns and student feedback data in ideological and political education classrooms. It reveals that the content of the ideological and political theory system is complex and diverse, and deep learning can promote students' higher-order thinking skills, enabling them to independently identify and analyze problems during practical exercises.

Some scholars contend that technological advancement has propelled the comprehensive development of ideological and political education. They assert that the era of artificial intelligence has arrived, with emerging technologies continuously driving revolutionary restructuring in the paradigms, concepts, delivery methods, and content of ideological and political education. This enables the realization of ideological and political education that is all-encompassing, continuous, inclusive, and fully effective. Reference [7] employs AI-assisted interactive modeling (Al-IM-loT) on an IoT platform to generate an intelligent system for ideological and political education. This system aims to shape students' political qualities, moral character, and sense of social responsibility to enhance educational outcomes. Reference [8] developed an AI-based intelligent system for higher education ideological and political education. This system effectively addresses management issues such as monotonous teaching methods, unscientific evaluation mechanisms, and lagging administration from both macro and micro perspectives. Reference [9] combined backpropagation neural networks with human behavior recognition models to construct an AI-driven online education algorithm. This algorithm aims to optimize higher education ideological and political education by extracting learning characteristics and monitoring students' real-time behavior. Reference [10] leveraged association rules between data mining and AI technologies to optimize the course environment for ideological and political education in higher education. It proposed four mechanisms—systematic design, team collaboration, environmental development, and quality management—along with a “three-stage, all-encompassing network IPE architecture” as a remedial measure to enhance the efficiency of ideological and political education in universities. Reference [11] proposes a web-based ideological and political education system for university students. This system utilizes multimedia service architecture and deep learning technology to evaluate and improve students' political education, thereby overcoming fixed spatial and temporal constraints. The academic community lacks clear definitions and explanations regarding the connotation and extension of the intelligent development of ideological and political education.

Existing research primarily focuses on the opportunities and challenges that intelligent technologies such as deep learning and big data present for ideological and political education and related work. It is evident that research on the intelligent development of ideological and political education has yet to form a complete theoretical framework.

This paper employs deep learning techniques to mine student learning data during ideological and political education in courses. By analyzing interaction patterns between students and ideological and political knowledge points, it investigates their mastery of knowledge during the learning process. Through manual annotation, it verifies the authenticity of knowledge point data to establish a comprehensive ideological and political knowledge dataset. Integrating visual and linguistic modalities, it performs text encoding preprocessing for knowledge points, consolidates named entities and entity relationships within ideological and political course content, and constructs a multimodal interaction architecture. The Knowledge Tracking Model (TCKT) is designed to embed student performance metrics—such as answer accuracy and response time—as interaction features. Combined with a learning behavior simulation module and two temporal channels, it captures the dynamic evolution of students' actual knowledge states during interactive learning.

2 Deep Learning-Based Method for Tracking Ideological and Political Knowledge

2.1 Research on Information Extraction Methods for Course-Based Ideological and Political Education

2.1.1 Analysis of Course Ideological and Political Education Datasets

Leveraging deep learning technologies to advance the intelligent development of ideological and political education information extraction first requires annotating relevant ideological and political knowledge to construct corresponding course-based ideological and political education datasets. Subsequently, through visual-language multimodal interaction design, text encoding, and pre-training, corresponding knowledge points within course-based ideological and political education are integrated. This facilitates knowledge tracking research through interactive feature mining.

For this annotation task, a dedicated annotation team composed of project members was formed. To eliminate subjective human errors and minimize data discrepancies, all sample data were annotated simultaneously following standardized annotation protocols. Upon completion, annotation consistency was evaluated using Cohen’s Kappa formula (1).

$$k = \frac{P_o - P_e}{1 - P_e} \tag{1}$$

Among these, P_o represents the ratio of annotators reaching agreement, calculated as per formula (2). P_e denotes the random probability of annotators reaching agreement, computed as per formula (3).

$$P_o = \frac{a + b}{n} \tag{2}$$

$$P_e = \frac{(a+b)\times(a+c)+(c+d)\times(b+d)}{n^2} \tag{3}$$

Among these, a represents the number of samples where both annotators produced identical results; b denotes the number of samples where Annotator 1 labeled as true and Annotator 2 labeled as false; c indicates the number of samples where Annotator 2 labeled as true and Annotator 1 labeled as false; d signifies the number of samples where the annotators produced inconsistent results.

2.1.2 Overall Architecture

Existing methods for Chinese information extraction have relatively few designs tailored for multimodal content, and there remain shortcomings in sequence modeling for visual information and in designing visual-language multimodal interactions. Therefore, this paper proposes a visual-language multimodal interaction architecture for the joint extraction of named entities and entity relationships in course-based ideological and political education.

The architecture comprises a text encoder, a character rendering module, a character sequence encoder, and a multimodal routing interaction module. To achieve joint extraction of named entities and entity relationships within a unified framework, a Global Pointer Network module based on Global Pointers is employed for entity extraction and relationship extraction decoding.

Compared to traditional relation extraction methods, this approach integrates visual-modal Chinese character glyph information, performs sequence modeling on glyph sequences, and employs a multimodal routing interaction module based on gated networks to efficiently blend effective information from both modalities.

2.1.3 Text Encoding

Figure 1 illustrates the text encoding architecture of the proposed method. Chinese-BERT-wwm is employed as the initial pre-trained model, with its built-in tokenizer used for word segmentation. This approach enables clearer boundary handling for complex Chinese ideological and political knowledge point word combinations.

Let W denote the sequence of tokens resulting from the Tokenizer processing the input raw text, with a maximum input length of n, such that $W = \{w_1, w_2, \ldots, w_n\}$. TokEmb represents the text content embedding layer, SegEmb denotes the input segment embedding used to characterize the overall embedding of different sentences, and PosEmb represents the positional encoding of each tokenization result. The final input to the BERT encoder can be represented as $I_t = \{I_1, I_2, I_i, \ldots, I_n\}$, where the input embedding I_i for each position is defined as shown in Equation (4).

$$I_i = TokEmb(w_i) + SegEmb(w_i) + PosEmb(w_i) \tag{4}$$

The output text feature representation Q_t is encoded by the BERT encoder on the input I_t and can be expressed in the form of formula (5).

$$Q_t = BERT(I_t) \tag{5}$$

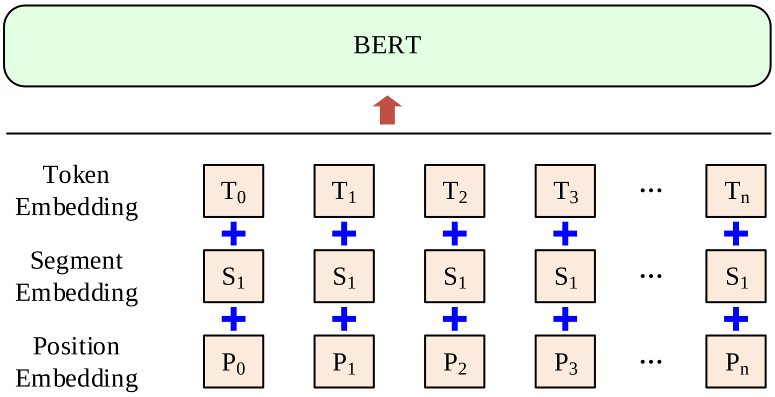


Figure 1: Text Encoding Architecture

2.2 Knowledge Tracking Model Based on Consistency Representation for Sequential and Causal Reinforcement Learning

2.2.1 Feature Input

After constructing the ideological and political knowledge point dataset, we designed a knowledge tracking model (TCKT) based on temporal and causal reinforcement learning consistency representation. Within TCKT, to enrich the features of input embeddings, this study considered the following elements: questions, knowledge concepts, answers, and question difficulty. Integrating these elements formed the learner's interaction feature embeddings.

1) Question Difficulty

The difficulty of a question can measure the average mastery level of students regarding the corresponding knowledge point. Generally, when learners provide incorrect answers during practice, it indicates cognitive barriers to understanding the question. Therefore, the accuracy rate of responses can to some extent reflect the difficulty of the question. Additionally, questions vary in popularity—that is, the frequency of responses differs. To balance this, this study defines the difficulty dif of each question based on Bayesian estimation theory, as follows:

$$dif_{q_t} = \frac{NE_{q_t}}{NE_{q_t} + m} D_{q_t} + \frac{m}{NE_{q_t} + m} TD \tag{6}$$

where D_{q_t} is the answer accuracy of the question q_t, NE is the number of times q_t was answered, m is the average number of times all questions were answered, and TD is the average answer accuracy of all questions.

2) Interaction embedding

Interaction embedding is the embedding of the basic interaction unit, which is the main component of the students' learning process, and is the feature of the Civics knowledge that can be acquired through answering questions. In this study, $q_t \in R^{d_k}$ is randomly initialized as the embedding of the question q_t, which is allowed to learn automatically in the training process. Thus, all problems can be transformed into an embedding matrix $Q \in R^{N \times d_k}$, where N is the number of problems and d_k is the dimension. Similarly, we use $c_t \in R^{d_k}$ as an embedding of the knowledge concept c_t, and $dif_{q_t} \in R^{d_k}$ as an embedding of the difficulty of the question dif_{q_t}. For question responses, this study expands them into all-zero or all-one vectors $a_t \in \square^{d_a}$

depending on whether they are answered correctly or not, and d_a is also dimensional. To obtain the interaction embedding $x_t \in R^{d_k}$ of the basic interaction units $(q_t, c_t, dif_{q_t}, a_t)$, we collocate q_t, c_t, dif_{q_t}, a_t and deeply fuse them with a multilayer perceptual machine (MLP). The details are as follows:

$$x_t = W_x^T \left[q_t \oplus c_t \oplus dif_{q_t} \oplus a_t \right] + b_x \tag{7}$$

Here $\oplus$ denotes the splicing operation, $W_x \in \mathbb{R}^{(3d_k + d_a) \times d_k}$ is the weight matrix, and $b_x \in \mathbb{R}^{d_k}$ is the bias term.

2.2.2 Learning behavior simulation module

In general, learners' state of Civics knowledge is constantly changing during the learning process, i.e., the length of response time for completing an answer, and the length of the interval between two interaction items can affect the characterization of learning consistency. Therefore, this study proposes a Learning Behavior Simulation (LBS) module. Specifically, we believe that the response time affects the learning process, while the interval time affects the learner's forgetting process of knowledge. Therefore, based on the characteristics of temporal data, this study first discretizes the former in seconds and the latter in minutes on the time scale. Then, we represent these two temporal features with the embedding matrices $rt \in R^{d_r \times d_k}$ and $it \in R^{d_{it} \times d_k}$. Where d_{rt} and d_{it} denote the number of response times and the number of intervals, respectively, the two temporal features rt_t and it_t corresponding to the learning interactions at time t can be represented by the vectors $rt_t \in R^{d_k}$ and $it_t \in R^{d_k}$ representations.

Each interaction usually corresponds to a different problem, and the corresponding knowledge state is updated differently. In order to match the learning interactions and knowledge states at moment t, we first multiply the knowledge state at the previous moment with the knowledge correlation vector QC_{q_t} related to the current problem to generate the fitness knowledge state $\hat{h}_{t-1}$:

$$\hat{h}_{t-1} = QC_{q_t} \cdot h_{t-1} \tag{8}$$

where $\cdot$ denotes the elemental product.

Inspired by LSTM, this study designs two time-domain channels, i.e., input gate and forgetting gate, to simulate learners' knowledge acquisition and forgetting behaviors during long-term learning. First, for the Civic knowledge forgetting part, we fused the causal interaction embedding, the previous moment of fitness knowledge state and the interval time, and then input the obtained vectors into the forgetting gate to simulate the process of learners' knowledge forgetting:

$$lf_t = \sigma\left(W_{lf}^T \left[\hat{h}_{t-1} \oplus \left(W_f^T \left[it_t \oplus \hat{x}_t \right] + b_f \right) \right] + b_{lf} \right) \tag{9}$$

where σ is the nonlinear activation function, $W_{lf}^T \in R^{2d_k \times d_k}$ and $W_f^T \in R^{2d_k \times d_k}$ are the weight matrices, $b_f \in R^{d_k}$ and $b_{lf} \in \mathbb{R}^{d_k}$ are the bias terms, $lf_t \in R^{d_k}$.

For the knowledge acquisition part, similarly, we combine the causal interaction embedding, the fitness knowledge state in the previous moment, and the response time. Then, we simulate the learner's process of absorbing the acquired knowledge as follows:

$$li_t = \tanh\left(W_{li}^T\left[\hat{h}_{t-1} \oplus \left(W_i^T\left[rt_t \oplus \hat{x}_t\right] + b_i\right)\right] + b_{li}\right) \tag{10}$$

where tanh is the nonlinear activation function, $W_{li}^T \in R^{2d_k \times d_k}$ and $W_i^T \in R^{2d_k \times d_k}$ are the weight matrices, $b_i \in R^{d_k}$ and $b_{li} \in \square^{d_k}$ are the bias terms, $li_t \in \square^{d_k}$.

Since the knowledge acquired by a person does not completely change his/her knowledge state, we design an input gate to control the ability of knowledge acquisition:

$$\eta_t = \sigma\left(W_{l\eta}^T\left[\hat{h}_{t-1} \oplus \left(W_\eta^T\left[rt_t \oplus \hat{x}_t\right] + b_\eta\right)\right] + b_{l\eta}\right) \tag{11}$$

where $W_{l\eta}^T \in \square^{2d_k \times d_k}$ and $W_\eta^T \in \square^{2d_k \times d_k}$ are the weight matrices, $b_\eta \in \square^{d_k}$ and $b_{l\eta} \in \square^{d_k}$ are the bias terms, $\eta_t \in \square^{d_k}$.

In order to obtain the student's knowledge state h_t after the learning interaction at time t, we multiply η_t and li_t to get the actual knowledge acquired by the learner, and add the effect of forgetting factor to the knowledge state at the previous moment as follows:

$$h_t = lf_t \cdot h_{t-1} + \eta_t \cdot li_t \tag{12}$$

2.3 A study of deep learning knowledge tracking in the process of teaching and learning curriculum Civics

2.3.1 Analysis of data sources

The data for this study come from four Civics courses taken by learners on the online education platform, including “Introduction to the Basic Principles of Marxism,” “Theory and Practice of Socialism with Chinese Characteristics in the New Era,” “Outline of Modern Chinese History,” and "Fundamentals of Ideological and Moral Cultivation and the Law. “Outline of Modern Chinese History” and “Civic and Moral Cultivation and Legal Foundation”. Historical data of learners' answers in two natural semesters, Spring 2024 (dataset denoted as D) and Fall 2024 (dataset denoted as D'), with a total of 12,500 participants. The statistical attributes of each dataset are the number of learner users and the number of question-answering interactions, respectively.

2.3.2 Data pre-processing

Firstly, the original datasets D and D' are cleaned, if the percentage of missing values of a data is greater than or equal to 50.00%, the data is removed, otherwise the data is retained and filled with missing values. Secondly, the outliers in both the datasets are removed, for the same learner ID the number of answers to the same practice question is higher than 15 times, it is considered as outlier data. Again, the two datasets are normalized. Finally, multiple duplicate data for the same learner are merged and identified based on the learner ID to get a total of 3500 learner users who are studying four courses at the same time and have a valid answer count of 10950.

3 Deep Learning Based Civic Knowledge Tracking Practice

3.1 Analysis of the results of the annotation of knowledge points

After manual annotation and preprocessing of the text by the members of the group, the main knowledge point datasets of the four Civics courses were established. Table 1 shows the number of samples corresponding to the knowledge point entities. According to the type of Civics designed by the Visual Language Multimodal Interaction Architecture, after labeling and screening, there are 30 instances of Civics elements, and the total number of samples of these 30 instances is 2,231. This sample number basically covers the main knowledge points of the four Civics courses, which can better connect the knowledge points of different relationships and facilitate students' interaction in the learning process.

Table 1: Number of samples corresponding to the knowledge point entities

Tag number	Label name	Data volume	Tag number	Label name	Data volume
1	Tolerance	85	16	Cultural inheritance	80
2	Responsibility Love	67	17	Technological utilitarianism	76
3	Patience	80	18	Technological humanitarianism	65
4	Self-reflection	59	19	Technological patriotism	58
5	Self-control	64	20	Scientific ethics	59
6	Modesty	72	21	Labor spirit	78
7	Honesty	68	22	Devotion spirit	82
8	Strength	78	23	Pragmatic spirit	71
9	Peacefulness Exploit	62	24	Exploration spirit	73
10	Diligence	70	25	Engineering thinking	80
11	Optimism Confidence	58	26	National enterprise	90
12	Persist in the leadership of the Party	76	27	Legal awareness	89
13	Persist in the path of socialism with Chinese characteristics	80	28	Resilience	84
14	Protect the environment	82	29	Patriotism	86
15	Optimism Confidence	78	30	Innovative spirit	81
Total number of labels			Total data volume		
30			2231		

3.2 Knowledge tracking model performance test

3.2.1 Comparison of performance with the baseline model

After the dataset is constructed, in order to evaluate the performance of the model in this paper, the TCKT is analyzed on this dataset in a comparative experiment with the baseline model. The results of the comparison experiments with the baseline model are statistically presented in Table 2. The TCKT knowledge tracking model, which is based on temporal and causal enhancement of learning consistency, achieves better performance than the other baseline models in all four metrics. The TCKT reached 90.10 on the Hits@5 indicator, 92.97 on the

Hits@10 indicator, 94.43 on the Hits@15 indicator, and 90.57 on the MRR indicator. It is the only model among the six where all metric values exceed 90. TCKT's advantage in knowledge tracking performance lies in embedding interactive features such as problem difficulty and incorporating additional reference objects. Simultaneously, by simulating input and forgetting processes through its behavioral simulation module, it continuously updates learning interactions and knowledge states, thereby enhancing the accuracy of ideological and political knowledge tracking.

Table 2: Baseline model comparison experiment results

Comparison method	Hits@5	Hits@10	Hits@15	MRR
JAPE	51.56	85.72	87.19	61.41
GCN-Align	51.63	85.64	87.11	67.32
HGCN	70.41	85.96	87.42	89.24
KECG	58.18	84.76	86.24	72.25
HyperKA	67.58	90.76	92.25	80.36
TCKT	90.10	92.97	94.43	90.57

3.2.2 Ablation Experiment

To thoroughly investigate the impact of each design element within the TCKT model on knowledge tracking experiment outcomes, an ablation analysis was conducted to enhance the model's reliability and validity. Table 3 summarizes the ablation analysis results. Except for the complete model in the second row, each subsequent row represents progressively removing the corresponding module from the preceding row. After removing the Input and Forgetting time channels, the model's four metric values decreased from >90 to the 80-90 range. Following ablation of the Learning Behavior Simulation (LBS) module, metric values dropped from the 80-90 range to the 70-80 range. After the interaction embedding module was ablated, the values dropped further to the 65-70 range. When the feature input module was also ablated, the metric scores ultimately remained only within the 60-65 range. This indicates that the two temporal channels and LBS contribute most significantly to the TCKT model, followed by the interaction embedding and feature input modules. Overall, all four modules have a synergistic effect on the knowledge tracking experiment results of the TCKT model, forming an indispensable relationship.

Table 3: Analysis results of the ablation experiment

Medol	Hits@5	Hits@10	Hits@15	MRR
TCKT	90.10	92.97	94.43	90.57
Time-domain channel	83.82	85.60	87.40	82.08
LBS	75.74	76.39	78.42	71.25
Interactive Embedding	67.26	68.83	69.45	65.82
Element integration	60.39	62.41	64.21	63.26

3.3 Application Effectiveness of the Model in Ideological and Political Education Learning Interactions

3.3.1 Validity Test for Higher-Order Information Analysis

To evaluate the models' information extraction effectiveness and interaction levels during student responses, the TCKT model and the comparative model GTMKT were selected to analyze their probability of correctly predicting exercises. Figure 2 displays the prediction probabilities of TCKT and GTMKT on the dataset. Rows represent models, while columns denote exercise ei and its corresponding key concept c_i. Across the consecutive 12 exercises e_1-e_{12}, TCKT's prediction probabilities ranged from 0.61 to 0.69, while GTMKT's ranged from 0.47 to 0.54. TCKT exhibits higher prediction probabilities. This stems from its feature input stage, where factors like question difficulty are controlled, and interactions between elements are more tightly integrated. For instance, during practice, students can learn key concept knowledge c_2 through exercise e_1. Even if their accuracy doesn't reach 1, they still acquire conceptual knowledge, improving their answer accuracy in subsequent exercises while simultaneously enhancing the model's predictive probability for practice exercises.

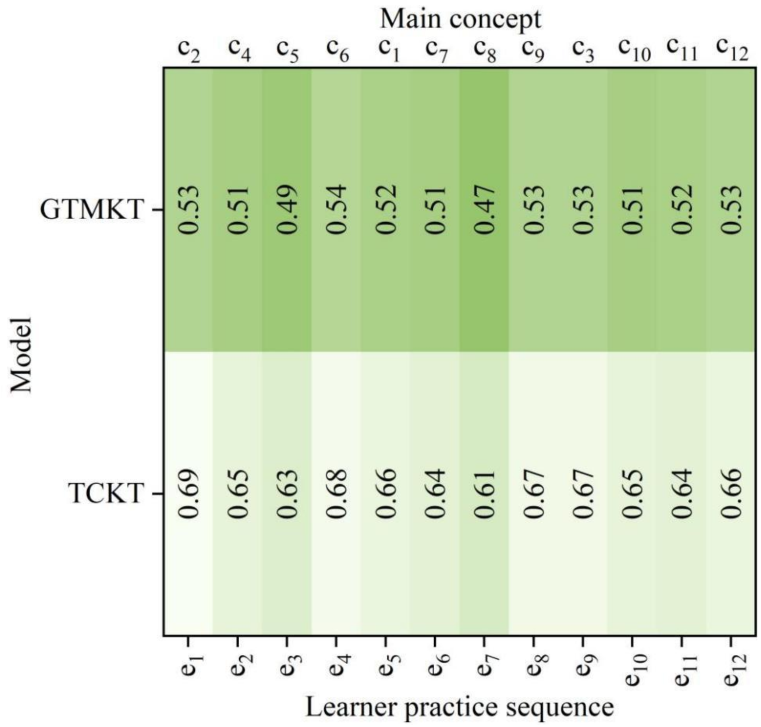
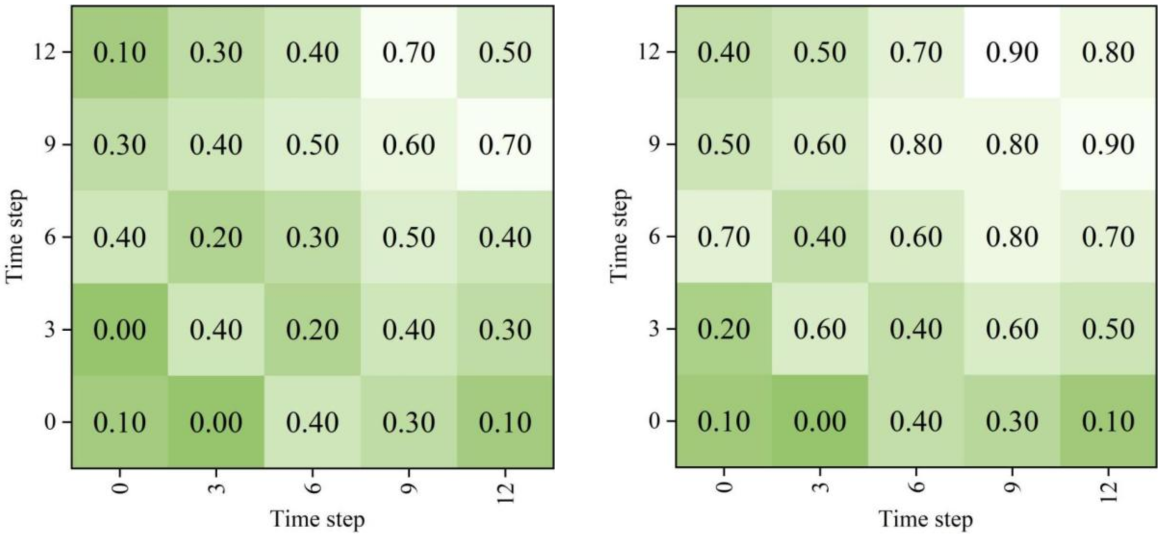


Figure 2: The prediction probabilities of TCKT and GTMKT on the dataset

3.3.2 Effectiveness Verification of Learning Behavior Simulation

In the learning behavior simulation module of TCKT, two temporal channels—input gate and forget gate—are introduced to simulate the entire student interaction process. To further analyze how the TCKT model captures the global dependencies between practice and main concepts, node-local and global attention weights are predicted for 12 time steps. Figure 3 visualizes the local and global attention of concept nodes. In Figure 3(a), after removing the input gate and forget gate from the LBS module in TCKT, prediction probabilities cluster between 0.00 and 0.50, with only a few exceeding 0.5. These are confined to the exercise itself and neighboring concept nodes. Figure 3(b) shows that after embedding the input gate and forget gate of the LBS module into TCKT, prediction probabilities cluster between 0.40 and 0.80, with a small portion reaching 0.90. This clearly demonstrates that global dependencies can capture most of the past. This indicates that after introducing the input gate and forget gate of LBS, TCKT gains a broader perspective on interactions between knowledge concepts, enhancing knowledge point associations throughout the entire practice-concept map.



(a) Node local attention (b) Node global attention

Figure 3: Visualization of the local and global attention of concept nodes

Additionally, 300 student interaction sequences were randomly selected from datasets D and D`. After capturing global dependencies, feature dimensionality reduction was performed. Figure 4 visualizes the global dependency capture results from the practice-concept map. The left and right sides represent two response scenarios (incorrect and correct). It can be observed that practice-concept maps for correct responses primarily cluster on the right side of the scatter plot, while incorrect responses cluster on the left. This demonstrates that the exercise-concept map effectively captures student-exercise interactions through TCKT to predict future performance. Some cross-interaction points appear in the figure due to the complexity of learning interactions; performance cannot be estimated solely from exercises. For instance, students unfamiliar with relevant concepts may coincidentally answer an exercise correctly. Overall, the model can deeply track student responses and predict their mastery of knowledge points.

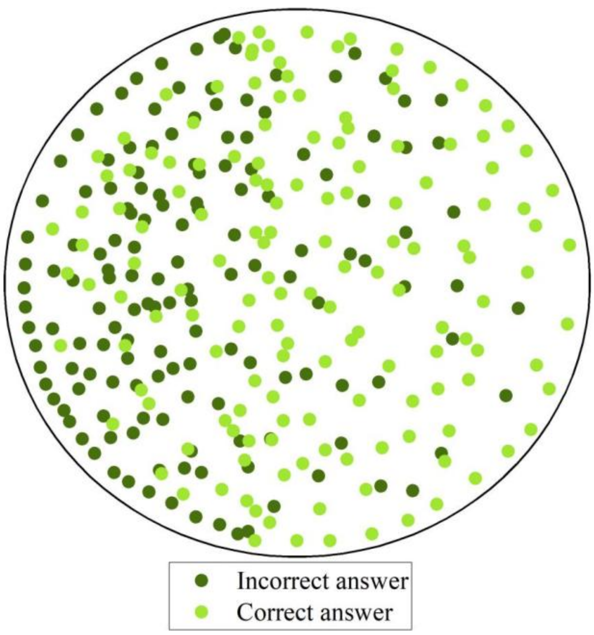


Figure 4: Practice - Concept Map Captures Global Dependencies

4 The Impact of Deep Knowledge Tracking on Students' Systematic Learning of Ideological and Political Education

To further clarify the impact of each module within the Deep Knowledge Tracking Model on students' systematic learning of ideological and political education, this study employs a stepwise regression method. Two time channels, LBS, interactive embedding, and feature input are treated as independent variables for multiple regression analysis.

Table 4 presents the regression analysis results for deep knowledge tracking and students' systematic learning outcomes in ideological and political education. R represents the coefficient of determination, with values closer to 1 indicating better fit. The data exhibits an R^2 of 0.802, meaning the independent variables explain 80.2% of the variance in the dependent variable, indicating a good fit. When $p < 0.05$, it indicates that the independent variables influence the dependent variable, meaning at least one independent variable affects the dependent variable. All p-values in this dataset are less than 0.01, confirming that each module of the deep knowledge tracking model influences the effectiveness of students' systematic ideological and political learning. All VIF values are below 10, indicating no severe multicollinearity issues. The VIF values in this dataset range from 1.753 to 4.294, all below 10, confirming no severe multicollinearity among independent variables. The formula for students' systematic learning outcomes in ideological and political education is: Students' systematic learning outcomes = 0.201 + 0.427 × 2 time channels + 0.394 × LBS + 0.109 × interactive embedding + 0.070 × feature input.

Table 4: Knowledge tracking and regression analysis of learning outcomes

Medol	Unstandardized coefficient		Standardized coefficient	T	Sig.	Collinearity statistics	
	B	Standard error	Beta			Tolerance	VIF
(Constant)	0.201	0.093	-	1.293	0.641	-	-
Two time channels	0.427	0.025	0.418	3.475	0.001	0.209	4.294
LBS	0.394	0.037	0.375	3.012	0.001	0.312	3.826
Interactive embedding	0.109	0.010	0.120	1.023	0.003	0.345	2.361
Feature input	0.070	0.008	0.087	0.938	0.003	0.329	1.753
R^2			0.802				
F			82.391				
P			<0.01				
Dependent variable: The effect of students' systematic learning of ideological and political education							

5 Conclusion

This paper designs the Knowledge Tracking Model (TCKT) to investigate students' knowledge dynamics in ideological and political education through deep learning techniques. A dataset comprising 2,231 samples was constructed by annotating 30 knowledge points across four required ideological and political courses. Among six models compared, TCKT demonstrated optimal knowledge tracking performance, achieving scores of 90.10, 92.97, 94.43, and 90.57

across four metrics, validating its effective knowledge tracking capability. Through interactive analysis of exercises and conceptual knowledge, the model achieves a 61–69% probability in predicting students' knowledge states. 90.57, validating its strong knowledge tracking efficacy. Through interactive analysis of practice and conceptual knowledge, the model achieves 61–69% probability in predicting students' knowledge states, demonstrating broader attention to overall interactions and superior global focus performance. Deep knowledge tracking positively influences students' systematic learning outcomes in ideological and political education at the 80.2% significance level (P<0.01), with no multicollinearity issues. Tracking students' response data using the TCKT model enables relatively accurate prediction of their mastery of ideological and political knowledge, providing scientific basis for subsequent teaching adjustments.

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