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Innovative Research on Artificial Intelligence-Driven Art Design Education Courses

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Abstract In art and design education, students' learning paths present diversified characteristics, and there are significant differences in the degree of knowledge mastery. In this paper, a DKVTMN-DTCN knowledge tracking model is constructed, which realizes accurate tracking of students' knowledge status in art and design education courses by integrating temporal convolutional network and forgetting mechanism. The model adopts a dual-feature processing architecture, using TCN to process temporal feature data and CART decision tree to process non-temporal feature data, and introduces a forgetting time effect mechanism for learning ability differentiation on the basis of the DKVMN baseline model. The experimental results show that on the DPA_2023 dataset, the AUC of the DKVTMN-DTCN model reaches 0.8358 and the ACC reaches 0.9358, which is improved by 2.44% and 0.06%, respectively, compared with the best-performing SPKT method. On the PP_2023 dataset, the model's recall reaches 0.9921 and F1 score reaches 0.9790, both of which outperform the existing baseline method. The knowledge state analysis shows that the model can effectively capture students' forgetting behavior in discontinuous learning periods, which is in line with the law of Ebbinghaus' forgetting curve. This study provides technical support for intelligent curriculum optimization in art and design education, which helps to realize personalized teaching and accurate learning assessment, and promotes the development of the education model in the direction of data-driven intelligence.

Index Terms Knowledge tracking model, temporal convolutional network, forgetting mechanism, art and design education, intelligent curriculum, personalized teaching

I. Introduction

Modern art and design originated from the Bauhaus School of Art and Design in Germany, which is the first art and design institution in the world, which not only put forward the earliest artistic viewpoints and theories, injected a brand-new soul into the early art and design, but also cultivated the earliest batch of designers and artists, and created a brand-new era for the world's art and design [1]-[3]. China's art and design education originated in 1928, which is not too late compared with western countries. The first real art and design education institution in China was the National Academy of Fine Arts (now known as the China Academy of Art), which had art and design majors in the real sense only in 1958 [4], [5]. Gradually, art and design education in the world after decades of rapid development, has its own series of basic and professional courses, but the major art and design colleges and universities in the specific curriculum have different places, it is this difference makes art and design students are subjected to the education mode and objectives are not very clear and perfect [6]-[8].

The types of courses in art and design education and teaching, such as the setting of compulsory and elective courses, basic and professional courses, theoretical courses and practical courses, as well as the optimized structure of their balance, comprehensiveness and selectivity, are the concretization of the goals of art and design courses, which ensures the realization of the goals of the courses by establishing the proportionality of various subjects in the course system [9]-[11]. And the rationality or otherwise of the curriculum structure setting is directly related to whether the art and design education curriculum system can be carried out smoothly, which is the specific embodiment of the talent cultivation mode. With the arrival of the intelligent era, the original education curriculum can no longer meet the needs of contemporary students. The coverage rate of generative artificial intelligence in commercial art design is more than 70%, but the teaching materials and curriculum lag is serious, resulting in less than 20% of the syllabus about artificial intelligence [12], [13].

In addition, in the AI environment, art design works can be generated by AI assistance, but teachers are difficult to accurately distinguish between human independent creation and AI-assisted generation, which is not conducive to the benign development of education [14], [15]. And with the rapid development of artificial intelligence technology, deep learning has been widely used in various fields. In the field of education, the application of deep learning is promoting the reform and innovation of education, optimizing the traditional education model with the application of personalized education, intelligent assessment, intelligent tutoring and intelligent management, improving the effect and quality of education, and providing a new path for the art and design education curriculum [16]-[18].

This study proposes a knowledge tracking model optimization scheme that integrates deep learning techniques. The study mainly includes three levels: first, for the multimodal characteristics of art and design education data, a dual feature processing architecture is designed to deal with temporal and non-temporal data separately to ensure that the model can make full use of different types of information about learning behaviors; second, a temporal convolutional network is integrated into the classical DKVMN model to enhance the model's ability to deal with sequential data, and at the same time, the mechanism of forgetting is introduced to make the model more consistent with the difference in learning ability. forgetting mechanism, so that the model is more in line with real learning scenarios; finally, the effect of the model is verified through actual teaching data, and its application value in the prediction of learning performance, knowledge state tracking and other aspects is analyzed, so as to provide technical support and theoretical guidance for the curriculum innovation and structural optimization of the art and design majors.

II. Model for tracking student knowledge in art and design education programs

II. A. Deep Learning Related Technologies

II. A. 1) Knowledge tracking algorithm

Knowledge tracking algorithms are widely used in the field of education, which can model learners' knowledge mastery based on their historical learning records, track the changes in students' knowledge status as they continue to learn and practice, make accurate assessments of students' learning effects at the knowledge point level, and then predict students' future question-answering performance. The knowledge tracking task is often formulated as a supervised sequence learning problem, in which the probability of correctly answering a new exercise question is predicted for each learner's history of answering sequences $X=\{x_1,x_2,\ldots,x_{n-1}\}$, i.e., $P(r_t=1|r_t,X)$.

The main knowledge tracking algorithms that have been studied and extended by scholars are BKT, DKT, and DKVMN, among which the DKVMN model has a better performance.The BKT algorithm models each knowledge point individually, considers that there is no relationship between the knowledge points, treats the student's comprehension of the knowledge point as a binary variable, and updates the knowledge state of the student through the results of his/her answers to the questions and then predicts whether the student will correctly answer the next question or not. answer the next question. However, it ignores the influence of the students' question order and the correlation between the questions on the prediction results, and thus the prediction accuracy is not high, in addition, the BKT algorithm needs to pre-label the correspondence between each exercise and the knowledge point, which greatly increases the task of manual labeling.The DKT algorithm uses recurrent neural networks (RNN) to track the students' understanding of the knowledge point and achieves a good prediction result, when the student practice, it will use the information of previous time points to predict the performance of students in doing the questions. However, problems such as large number of parameters, long training time, and difficulty in directly outputting the understanding of individual knowledge points due to modeling students' knowledge states through hidden layers hinder further development and application of the algorithms. The DKVMN model adds an external memory to avoid the correlation between the training parameters and the model's storage capacity, and the network's sequential modeling ability is improved, and it achieves good predictive results in knowledge tracking tasks compared to BKT and DKVMN [19]. better results than BKT and DKT. Memory Augmented Neural Network (MANN) achieves better memory capability than RNN and LSTM by adding a memory matrix to a normal recurrent neural network to improve the network's memory capability, adding the read process and the write process to control the updating of the knowledge state.DKVMN, based on the MANN algorithm, is designed to have a static key matrix to store the knowledge concepts in the memory, and another dynamic value matrix to store and update the student's understanding of each knowledge concept, i.e., the knowledge state.The DKVMN model automatically learns the correlation between the input exercises and the underlying concepts, and at each timestamp only the corresponding concept state is stored and updated.

The operation process of the DKVMN model is divided into three parts: weight calculation, read process and write process. In the weight calculation part, the embedding vector of exercise label q_t and the inner product of the knowledge concept matrix M^k are calculated, and the correlation w_t weight between exercise q_t and related knowledge concepts is obtained by the Softmax function, which is applied to the correlation calculation in the reading process and writing process. In the reading process of the model, the reading vector r_t was obtained by calculating the weighting of the correlation weight w_t and the knowledge state matrix M^v, and the students' mastery of the related knowledge concepts of q_t was summarized to represent the mastery of the exercise q_t, and then r_t was spliced with the exercise embedding vector and then passed through the fully connected layer with the Tanh function and the Sigmoid function respectively to obtain the prediction probability p_t, which was used to predict the probability of the student's accurate answer to q_t. In the writing process, the joint tuples of exercise q_t and answer result y_t were embedded into the model, and then the embedding vectors were activated by the Sigmoid function and Tanh function to obtain the erasure vector e_t and the addition vector a_t, and e_t and a_t were used to update the knowledge state matrix M^v to obtain the new knowledge points of the art and design education course after the students completed the exercises.

II. A. 2) Forgetting mechanisms

In the field of educational psychology, many scholars recognize the importance of human forgetting behavior and study the influencing factors of forgetting.

Forgetting is a common phenomenon in the learning process and has an unavoidable impact on the degree of students' mastery of knowledge, and thus some researchers have devoted themselves to studying the phenomenon of forgetting in order to better analyze the state of students' knowledge and to assist them in improving their learning efficiency. In order to describe the change of memory over time, the German psychologist Ebbinghaus proposed the forgetting curve [20]. After experimental research, he found that the phenomenon of forgetting begins to occur after learning, and the speed of forgetting gradually slows down from very fast.

There are various mathematical representations of the forgetting curve. The forgetting curve studied by Ebbinghaus represents the retention rate of relearning and is best suited to represent the curve as a rapidly decaying power function. He has studied fitting the forgetting curve with the following function, where b denotes the retention rate of relearning and t is time. However, this function was generated under specific experimental conditions of learners, learning materials and learning process, so it cannot be applied to all experimental situations:

$$b = \frac{100k}{k + \log t^c} \tag{1}$$

The power function model fitting the forgetting curve can effectively reflect the change of the amount of knowledge remembered by students in the learning process over time, and most ecologically effective quantitative description of the forgetting law, whose formula is shown below:

$$\begin{aligned} R_t &= 0.19 + (1-0.19)\times 0.78 \times (1+T)^{-0.68} \\ &= 0.19 + 0.81 \times 0.78 \times (1+T)^{-0.68} \end{aligned} \tag{2}$$

where R_t denotes the degree of memory retention and T is the time interval between the current time and the last time the student learned the point.

II. B.Preprocessing modeling based on temporal multi-behavioral features

To address the lack of temporal behavioral feature preprocessing in most knowledge tracking models, this chapter proposes a preprocessing method based on temporal behavioral features. The method is based on the CNN [21] model with the addition of the applicable sequence model and memory history, which is the causal convolution network and the inflated convolution and residual module. Therefore, TCN is mainly composed of causal convolution, inflationary convolution and residual connection. Among them, causal convolution has two distinctive features:

(1) Future information is not considered.

(2) The longer the retrospective history information is, the more hidden layers it has and the more complex it is. To address this problem, the network structure utilizes inflated convolution to expand the sensory field, i.e., to allow a larger range of information to be included in the output of each convolution. When $d = 2$, it means that every two sampling points at the input take one as the input of the latter layer, the calculation of the expansion convolution is shown in the following equation.

$$F(s) = (X * df)(s) = \sum_{i=0}^{k-1} f(i) \cdot X_{s-di} \tag{3}$$

where d is the expansion factor, k is the convolution kernel size, and X_{s-d} denotes the past data.

II. C.Modeling temporal forgetting based on learning ability

The temporal forgetting method based on learning ability is mainly aimed at analyzing the different effects of large time intervals on students' forgetting characteristics under different students' learning abilities. In this section, the main purpose is to calculate the learning ability of students, and then study the forgetting pattern of students with different learning abilities under different time intervals.

Firstly, according to the preprocessing stage, i.e., the a priori results obtained through the processing of temporal behavioral features and non-temporal behavioral features, then the learning ability of students is obtained through calculation, and different forgetting responses are made according to different learning abilities and learning intervals of students. The specific formula for calculating students' ability is as follows.

$$R(x)_s = \frac{\sum_{i=1}^{k} x_i = 1}{|N|} \tag{4}$$

$$I(x)_s = \frac{\sum_{i=1}^{k} x_i = 0}{|N|} \tag{5}$$

$$S(x)_s = R(x)_s - I(x)_s \tag{6}$$

where $R(x)_s$ denotes the rate of students answering k questions correctly, $I(x)_s$ denotes the rate of students answering k questions incorrectly, $|N|$ denotes the total number of questions the students did, $x_i = 1$ denotes students answering correctly, $x_i = 0$ denotes students answering incorrectly, and $S(x)_s$ denotes the student's art and design education program Learning Ability.

This chapter sets the learning interval timestamp h_t during the writing process. This setting enhances robustness to large time intervals between input exercises. The write process is mainly an update operation of the student knowledge state. First, the crossover feature c_t and the learning ability $S(x)_s$ are jointly embedded in a B matrix $(2Q \times d_v)$ to obtain the knowledge growth v_t of the students with different learning abilities after completing this exercise. The writing process is divided into two main operations, namely erasing memory and adding memory. Erasing the memory represents the process of forgetting the knowledge concepts by the students:

$$v_t = B[c(q_t, g_t), S_t] + b_3 \tag{7}$$

$$z_t = w_3[v_t, h_t] + b_3 \tag{8}$$

$$e_t = sigmoid(E^T z_t + b_e) \tag{9}$$

$$\tilde{M}_t^v(i) = M_{t-1}^v(i)[1 - w_t(i)e_t] \tag{10}$$

where z_t is a knowledge growth vector with enhanced time effects. e_t denotes the erasure memory vector, $E(d_v \times b_e)$ is the transformation matrix.

Increasing memory represents the update of students' knowledge acquisition of related concepts through practicing and answering questions:

$$a_t = \mathrm{Tanh}(D^T z_t + b_a)^T \tag{11}$$

$$M_t^v(i) = \tilde{M}_{t-1}^v(i) + w_t(i)a_t \tag{12}$$

where a_t is a row vector, i.e., it is an add memory vector, this mechanism of erasing and then adding is in line with the changing state of knowledge of the art and design education program in which students forget and reinforce concepts during the learning process.

II. D.DKVTMN-DTCN model construction

DKVTMN-DTCN is mainly composed of input layer, feature processing layer, and prediction output layer. The structure of the model is shown in Fig. 1. There are two parts in the input layer, which are timing feature data and non-chronological feature data. The feature processing layer is mainly a temporal feature processing module and a non-temporal feature processing module, the former utilizes time convolution network to process temporal features; the latter utilizes CART decision tree to process non-temporal features. Finally, in the prediction output layer, DKVMN is used as the baseline, and the feature connection module and the enhanced forgetting time effect mechanism are added to predict the students' answers to the art and design education course.

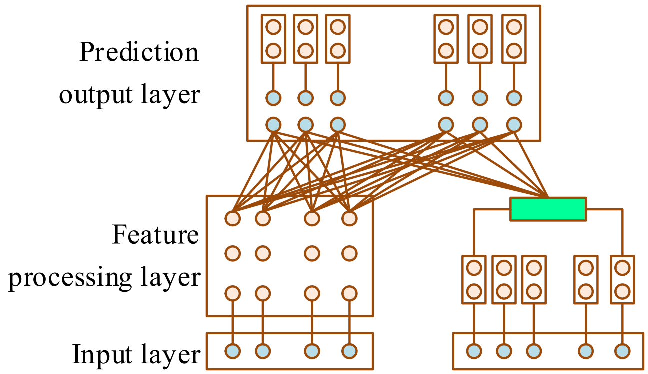

Figure 1: DKVTMN-DTCN model

II. D. 1) Input layer

The input layer mainly encodes the temporal feature data and non-temporal feature data into binary datasets for efficient processing of the feature data. The temporal feature data is $T_t(q_t, TD_t, r_t)$, where q_t is the label of the exercise, TD_t is the temporal feature, and r_t indicates whether the student answered the question correctly or not. For example, the question start timestamp and question end timestamp are temporal feature data; the non-temporal feature data are $G_t(q_t, GD_t, r_t)$, where q_t is the practice label, GD_t is the non-temporal feature, and r_t indicates whether the student answered the question correctly or not. Whether or not the student requested all prompts and the total number of times the student attempted to answer are non-temporal feature data.

II. D. 2) Feature processing layer

The feature processing layer consists of two main parts, the first part is to take advantage of TCN's powerful parallelism, flexible feeling field, stable gradient, and low memory to deal with the time-series problem, the specific algorithms have been elaborated in Section 3.1 of this chapter; the second part is to take advantage of the relatively small computation and easy to understand characteristics of the CART decision tree to deal with the non-timing problem.

II. D. 3) Predictive Output Layer

The prediction output layer mainly utilizes DKVMN to track the students' knowledge status and predict the students' answers.DKVMN, as a classical deep knowledge tracking model, utilizes a pair of key-value matrices for storing and tracking the knowledge concepts of the topics as well as the students' knowledge status, and the structure of the prediction output layer is shown in Fig. 2.

However, two important issues need to be considered when inputting the processed data from the feature processing layer to the prediction output layer: first, how to ensure the consistency of the data dimensions and sample size of these two datasets at the time of input; Secondly, there may be intervals of minutes, hours, or days before students answer the next question, which in turn may result in forgetting or increasing knowledge, and students have different learning abilities, which can directly lead to different levels of forgetting at different intervals for different students.

To solve these two problems, this chapter sets up a feature connection module in the input stage to solve the data input inconsistency problem.

(1) Feature concatenation module

The feature connection module crosses the timing a priori data with the non-timing a priori data by crossing them, and then the crossed features are used as the final input.

$$c(q_t, g_t) = f(G_t, T_t) \tag{13}$$

where $c(q_t, g_t)$ is the crossover feature, which includes preliminary a priori data corresponding to students. $f(\cdot)$ denotes the concatenation operation, implemented using the concatenate function in the keras model. G_t denotes the non-temporal a priori result. T_t denotes a temporal a priori result.

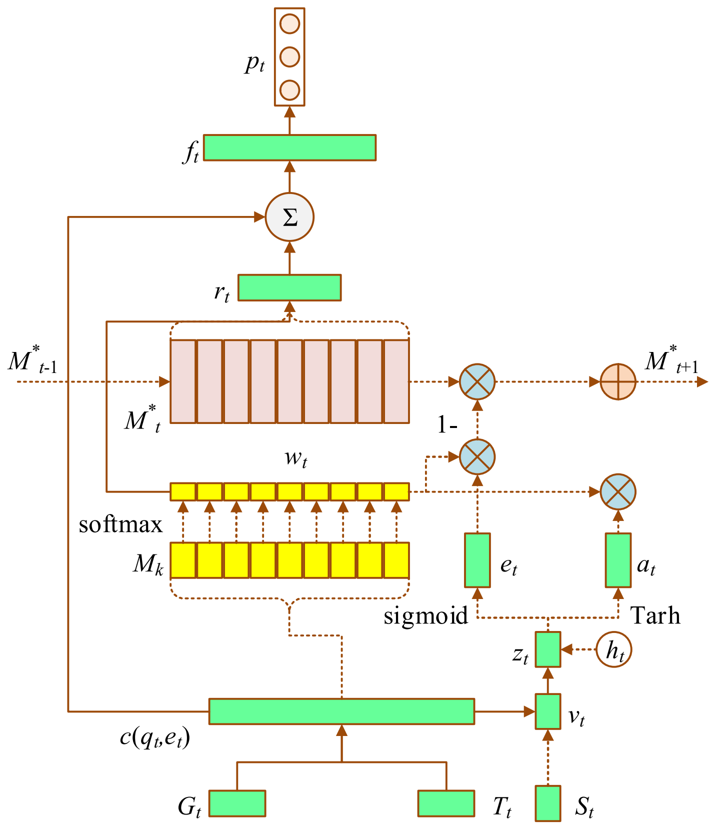

Figure 2: Forecast output layer structure

(2) Relevant weights

The simple one-way attention mechanism is mainly reflected in w_t:

$$w_t(i) = soft\max(c_t M^k(i)) \tag{14}$$

where the static matrix (M^k) is of size $N \times d_k$, and the data it stores is the potential concept information. The weight vector w_t represents the correlation between the exercise and each potential concept.

(3) Reading Process

The reading process focuses on probabilistic prediction of the answer situation by analyzing the conceptual information and outputs the predicted probabilities as results.

$$\gamma_t = \sum_{i=1}^{v} w_t(i) M_t^v(i) \tag{15}$$

$$f_t = \mathrm{Tanh}(w_1^T[\gamma_t, c_t] + b_1) \tag{16}$$

$$p_t = sigmoid(w_2^T f_t + b_2) \tag{17}$$

where γ_t is a summary of the student's mastery level of the exercise. The summary vector f_t contains the student's mastery level and the difficulty of the questions as well as the learning characteristics. Finally, the p_t scalar is obtained, i.e., the probability that the student will answer q_t correctly.

III. Experimental results and analysis of the student knowledge tracking model

III. A. Data sets and evaluation indicators

This chapter implements the DKVTMN-DTCN model and its comparison model in pytorch framework. In order to verify the advantages of the DKVTMN-DTCN model, this chapter uses AUC, ACC, recall (recall rate), and F1 (F1Score, reconciled mean) as evaluation metrics.

$recall$ and F1 are calculated as follows, where TP is the number of samples correctly categorized as positive samples, TN is the number of samples correctly categorized as negative samples, FP is the number of samples incorrectly categorized as positive samples, and FN is the number of samples incorrectly categorized as positive samples.

$$recall = \frac{TP}{TP + FN} \tag{18}$$

$$precision = \frac{TP}{TP + FP} \tag{19}$$

$$F1 = \frac{2 precision \cdot recall}{precision + recall} \tag{20}$$

The multimodal datasets required for the experiments in this chapter were collected from an online question answering platform under a real classroom. The dataset DPA_2023 is the question-answer records of the students in the Principles of Databases course in the year 2023, which includes 100 students, 60 questions, 20 skills, and 3,000 student answer records. The dataset PP_2023 is the question-answer records of the students of Python Programming course 2023, which includes 110 students, 60 questions, 10 skills, and 2700 student answer records.

III. B. Comparative Experiments

In order to verify the effectiveness of this chapter's model DKVTMN-DTCN fusing the forgetting mechanism with the applicable sequence model on the basis of DKVMN-DT, the heterogeneous graph-based knowledge tracking models GIKT, SGKT, and the heterogeneous graph-based knowledge tracking model SPKT based on the association of students' questions, which are mentioned in the related work, are used as the comparative experiments, based on the comparison between this chapter's model DKVTMN-DTCN and the three comparison experiments are all classification prediction tasks, the comparison experiments of the selection of AUC, ACC, recall, F1 four classification tasks on the evaluation index, as a measure of model performance. The epoch of all experiments was set to 400 pairs.

The model parameters were updated and iterated, and to avoid chance, all the results were obtained by five-fold cross-validation, and the specific values of the experimental results are shown in Table 1.

The DKVTMN-DTCN outperforms the baseline method in the comparison experiments on all four metrics for both datasets. Compared with the better-performing SPKT method, the model in this chapter improves 2.44%, 0.06%, 0.52%, and 0.05% on AUC, ACC, recall, and F1 in the DPA_2023 dataset, respectively, with the most significant performance enhancement on the ACC and F1 metrics. The model DKVTMN-DTCN in this chapter obtains the optimal performance on all four metrics in both datasets. In summary, it can be seen that this paper has positively impacted the knowledge tracking task of students in art and design education courses by adding the time convolution network and forgetting mechanism, which are more optimal for dealing with time series problems, to the DKVMN-DT model.

Table 1: Model comparison experiment

Data set	Model	AUC	ACC	recall	F1
DPA_2023	GIKT	0.7775	0.7858	0.8986	0.8655
	SGKT	0.7938	0.7665	0.8506	0.8465
	SPKT	0.8159	0.9352	0.9781	0.9660
	DKVTMN-DTCN	0.8358	0.9358	0.9832	0.9665
PP_2023	GIKT	0.7593	0.8151	0.9431	0.8358
	SGKT	0.7677	0.8284	0.9259	0.8932
	SPKT	0.7736	0.9292	0.9424	0.9611
	DKVTMN-DTCN	0.8208	0.9585	0.9921	0.9790

III. C. Analysis of students' knowledge status

In order to show the reasonableness of the model DKVTMN-DTCN for modeling students' knowledge states in this chapter, a section of question-answering sequence of a particular student was selected from the dataset DPA_2023 to track the changes in the degree of skill mastery during the question-answering process. Figures 3 and 4 show the heat maps of students' knowledge states presented by the SPKT model and the DKVTMN-DTCN model, respectively.

The horizontal coordinates in the graphs indicate the results of each student's answer, the vertical coordinates indicate the skill number, and the number of each cell in the heat map represents the student's specific mastery level. The darker the bottom color of the cell, the better the student's mastery of knowledge. Skill A is creative conception and concept generation skills, Skill B is drawing and modeling basic skills, Skill C is software application skills, Skill D is design expression and communication skills, Skill E is material and process cognitive skills, and Skill F is aesthetic and cultural understanding skills. And the students' answer records were spliced from four consecutive time periods.

Because of the high correlation between Skills A, B, and C, when a student answered a question correctly on one skill, the status of the other two skills would be elevated accordingly. At moment 19, the student answers the question related to skill C, and the knowledge status of skill A and skill B is subsequently elevated.The SPKT model simulates the effect of inter-knowledge correlations on the student's knowledge status.

The heat map of students' knowledge states under the DKVTMN-DTCN model inherits this point well, and the states of skills A, B, and C are synchronized and positively updated at the moment of moment 19. And different from the SPKT model, the student's learned knowledge state at moment 5, moment 9, and moment 14 shows an overall decrease change from the previous moment. This is due to the fact that moment 5, moment 9, and moment 14 are the starting position of a new set of exercises, which are discontinuous with the previous moment, with a long interval in between, and students are affected by the factor of forgetting, and the state of knowledge shows a decreasing trend. DKVTMN-DTCN adds the forgetting mechanism compared to SPKT, and can capture the effect of forgetting behavior on the state of knowledge, which fits the realistic scenario of innovation and structure optimization of art and design education courses, and proves that the improvement and design of the model are effective and reasonable.

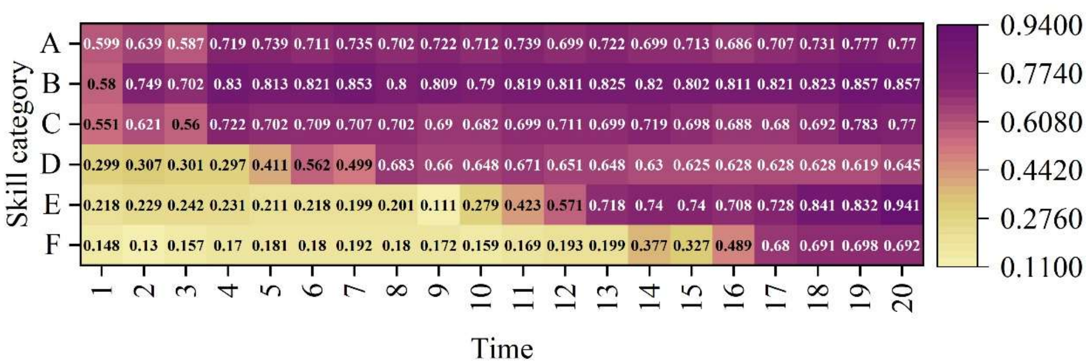

Figure 3: SPKT model knowledge state thermodynamic diagram

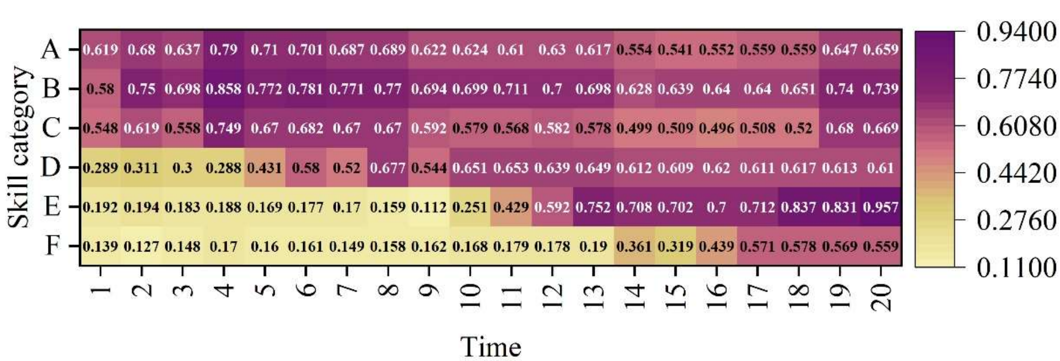

Figure 4: DKVTMN-DTCN model knowledge state thermodynamic diagram

III. D. Analysis of trends in the state of knowledge

Figure 5 shows a representation of the trend of knowledge state change. At moment 8~moment 9, students have learned skills A, B, C, D, so here we will compare the trend of knowledge state change between skill D and skills A, B, C. It can be observed in the figure that all the four skills are subject to the role of the forgetting curve in a downward trend, and the downward trend of D shows a more gentle state compared to skills A, B and C. At moment 13~moment 14, students have finished learning skill E. It can be observed that here, the downward trend of D and E is nearly the same, and both of them show a more gentle trend than A, B, and C. This is consistent with the Melabian communication model. This is in line with the research results of Merabian communication model and Ebbinghaus forgetting curve, which proves that this paper's modeling of the knowledge state of the students in the art and design education course fits the real scenario and is reasonable and effective.

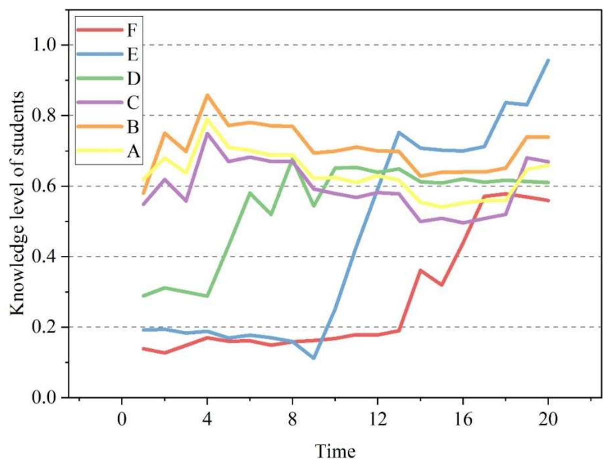

Figure 5: Dot line diagram of student knowledge status

IV. Specific pedagogical applications of the knowledge-tracking model

IV. A. Projection of learning achievement

In this section, the learner learning data from the datasets DPA_2023 and PP_2023 are used as an example, and both selected datasets are equally divided into front and back parts. The learner's learning probability P(T) is predicted by converting the mean value of all people's grades into a probability as the value of their knowledge mastery state P(Ln).

This part assumes that the learner's knowledge learning probability P(T) is constant throughout the learning process, and the teacher predicts the learner's knowledge status after the completion of the course knowledge learning before the end of the learner's course knowledge learning, so as to grasp the learner's course knowledge learning in a timely manner. This experiment applies the latter part of the learner learning data in the dataset DPA_2023 and the dataset PP_2023, and the results of the learner performance prediction are specifically shown in Table 2, through the performance prediction, the teaching strategy can be adjusted according to the learner's mastery of the knowledge of each course in a targeted manner. And when learners learn online, teachers can often set up targeted quizzes on various course knowledge exercises to collect more detailed information on learners' learning behavior, which will provide a convenient and reference for teachers to analyze and apply in future teaching. Note: $P(L1)=P(L0)+((1-P(L0))*P(T)*t)$.

Table 2: Learner's score prediction

Data set	Section	Initial probability P(L0)	Learning probability P(T)	Time t	Knowledge of the state P(Ln)
Data set DPA_2023	Low	0.16	0.75	1	0.7900
Data set DPA_2023	Medium	0.29	0.75	1	0.8225
Data set DPA_2023	Height	0.45	0.75	1	0.8625
Data set PP_2023	Low	0.1	0.85	1	0.8650
Data set PP_2023	Medium	0.25	0.85	1	0.8875
Data set PP_2023	Height	0.38	0.85	1	0.9070

IV. B. Learners' Average Knowledge Acquisition and Corresponding Prediction Accuracy

Based on the validity of the improvements to the knowledge tracking model verified in the previous section, the personalized knowledge tracking model with better prediction accuracy is applied in this subsection of the article to analyze the average knowledge mastery probabilities and their corresponding prediction accuracy AUCs derived from learners doing different amounts of questions in datasets 1 and 2. The specific results are shown in Fig. 6, and it is easy to find that the learners' knowledge mastery and model prediction accuracy predicted by the personalized knowledge tracking model change with the change in the amount of questions the learners do are also floating and changing. Especially when the question-answering data is long enough, the personalized knowledge tracking model can better distinguish between these two kinds of performance, and the curves of learner knowledge mastery and model prediction accuracy as the amount of questions are changed are in line with the learning pattern of the learner and the model prediction time, so it is considered that the learner cognitive diagnosis results given by the personalized knowledge tracking model on the two datasets are reasonable.

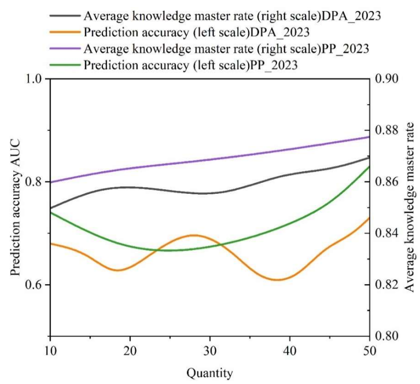

Figure 6: The trend of average knowledge and prediction accuracy

IV. C. Analysis of Average Knowledge Acquisition of Learners by Segments

In this subsection of the article, the segmented personalized knowledge tracking model with better prediction accuracy is applied to analyze the average knowledge mastery probability of learners in each segment in the dataset when they do different amounts of questions. Specific results are shown in Figure 7, which shows that the learners in the low and middle segments increase their knowledge mastery with the increase of the number of questions and stabilize; the learners in the high segment decrease their knowledge mastery with the increase of the number of questions and stabilize, and the phenomenon of mastery change of the learners in each segment reflects the ceiling effect, i.e., when approaching the top, the learners will naturally feel a layer of invisible barriers blocking their way to the top. That is, when approaching the top, they will naturally feel a layer of invisible obstacles blocking the top, so their mastery situation can only be up to a certain stage, and then it is impossible to continue to go up. This is the so-called glass ceiling barrier. The trend change in the learner cognitive diagnostic results given by using the segmented personalized knowledge tracking model on both data sets as the number of questions varied across segments of learners is acceptable.

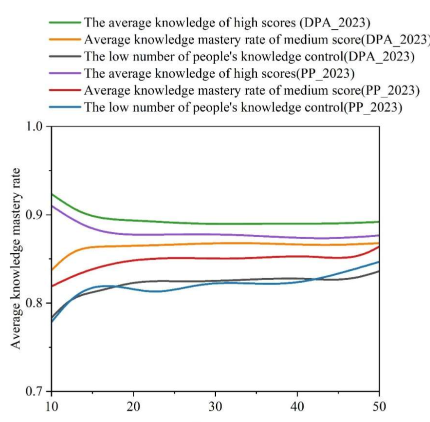

Figure 7: The average knowledge of each segment is mastered

V. Strategies for innovation and structural optimization of intelligent curricula for art and design majors

The biggest feature of the education model in the age of artificial intelligence compared with the traditional education model is that the speed of knowledge iteration is gradually accelerated. The step-by-step teaching mode is no longer adapted to the new law of knowledge production, and the design education in the age of artificial intelligence should be centered on cultivating innovation ability. Action learning method is more suitable for the new era of teaching practice, action learning method around the 721 theory of practice, that is, 10% of the time is used to learn theoretical knowledge and access to information; 70% of the time according to the theory of learning to practice, and in the process of practicing the trial and error; and the remaining 20% of the time is used for the exchange of experience. In the traditional art and design teaching model, learners are more as consumers of learning resources than as participants. As consumers, they lack the sense of participation in learning, and as passive recipients of knowledge, they spend a lot of time on knowledge learning, resulting in a lack of practical training and knowledge exchange. Nowadays, the development of self-media and online media allows learners to acquire knowledge in a variety of ways. Learners have the identities of both knowledge consumers and knowledge producers, which will effectively improve the learning efficiency of learners.

First of all, the large language model in AI technology can well design personalized teaching content for students. Teachers set learning nodes in advance, and the AI model gives targeted answers according to the questions raised by students, thus reducing teachers' working time.

Secondly, the AI model can update the knowledge database and generate corresponding training tasks in time to improve the updating speed of knowledge in course design. In the traditional teaching mode, teachers mainly teach theory by lecturing, and the use of AI technology helps to build a teaching mode that combines theory with practice. The human knowledge base is immense, and AI technology can assist teachers and students in rapid screening of knowledge content. In the teaching scenario of art design majors, the use of AI-assisted design software can reduce the cost of trial and error of different design drafts, and help design students realize the balance between rationality and aesthetics in design, so as to improve the design strategy.

At the same time, AI technology is also of great help to the construction of network online courses. The existing network online courses are generally characterized by the difficulty of teachers answering questions. The traditional network online courses mainly use video as the teaching carrier, but the video content is relatively fixed, which may not be suitable for the learning progress of each student. Therefore, online Q&A is particularly important. However, network online courses are characterized by a large number of students, and it is difficult for teachers to answer questions in a personalized way, while AI models with targeted training can solve this problem well.

In summary, the teaching mode of art design majors in the era of artificial intelligence should take action pedagogy as the main means, and combine with artificial intelligence technology to carry out online and offline hybrid teaching. The identity of students is not only a consumer of knowledge resources, but also a producer of knowledge resources, changing from purely learning theoretical knowledge to autonomously carrying out practical trial and error experience accumulation learning.

VI. Conclusion

The DKVTMN-DTCN model in this study shows significant advantages in the knowledge tracking task of art and design education courses. Experimental validation shows that the model achieves the leading level in all performance indicators when dealing with the DPA_2023 dataset containing 100 students and 3000 answer records, in which the recall indicator reaches 0.9832, which exceeds the existing baseline method. The ACC performance of the model reaches 0.9585 in the test with 110 students and 2700 records on the PP_2023 dataset, which proves its stability and generalization ability on datasets of different sizes. The results of the knowledge state analysis further confirmed the validity of the model, which was found to be able to accurately capture the students' knowledge decay phenomenon during non-continuous learning periods by tracking the six core skills, a finding that is highly consistent with the theory of forgetting curve in educational psychology.

The model performs well in the application of academic performance prediction, and the accuracy of knowledge state prediction for students of different ability levels is significantly improved, providing a reliable basis for teachers to formulate personalized teaching strategies. In terms of technological innovation, the introduction of temporal convolutional network effectively solves the limitations of the traditional model in dealing with long sequential data, and the design of differentiated forgetting mechanism based on learning ability is closer to the real teaching scenarios.

The study opens up a new path for the in-depth application of artificial intelligence in the field of art and design education, which is of great significance in promoting the transformation of the education model towards data-driven intelligence, and at the same time provides a technical framework and implementation experience that can be drawn on for the optimization of the curricula of other creative majors.

References

[1] Charnley, K. (2020). Art, design and modernity: the Bauhaus and beyond. Open Arts Journal, 9, 43-56.
[2] Ortega García, C. A. (2021). RECOGNITION OF THE BAUHAUS: ART, DESIGN AND TECHNIQUE, 1919-1933. Index: Revista de Arte Contemporaneo, (12).
[3] Esen, E., Elibol, G. Ü. L. Ç. İ. N., & Koca, D. (2018). Basic design education and Bauhaus. Turkish Online Journal of Design Art and Communication, 8.
[4] Yang, Y., & Wang, D. (2018, June). The Differences between Art and Design in Italy and China: Definition, Education and Practice. In 2018 2nd International Conference on Management, Education and Social Science (ICMESS 2018) (pp. 148-151). Atlantis Press.
[5] Shen, B., & Xuan, X. (2023, December). Exploration and Reflection on Design Research Methods in the design education in China's art academies: The preliminary exploration though World Building practice at China Academy of Art. In SIGGRAPH Asia 2023 Educator's Forum (pp. 1-5).
[6] Gao, Y. (2020). Blended teaching strategies for art design major courses in colleges. International Journal of Emerging Technologies in Learning (iJET), 15(24), 145-158.
[7] Yu, D., Wang, L., Li, W., & Sun, H. (2022, June). Teaching a Basic Design Class for Art and Design Freshmen: Course Design and Lessons Learned. In International Conference on Human-Computer Interaction (pp. 348-363). Cham: Springer International Publishing.
[8] Jones, D. (2018). Art and Design Pedagogy in Higher Education: Knowledge, values and ambiguity in the creative Curriculum. Design and Technology Education: An International Journal, 23(1), 104-108.
[9] Zhang, X. (2021). Innovation of art design education in the new era. International Journal of Emerging Technologies in Learning (iJET), 16(15), 168-180.
[10] Qian, C., Ye, J. H., & Lee, Y. S. (2022). The effects of art design courses in higher vocational colleges based on C-STEAM. Frontiers in Psychology, 13, 995113.
[11] Mamvuto, A., & Mannathoko, M. C. (2023). The changing African art and design curriculum: narratives from teacher education. Arts education policy review, 124(3), 149-156.
[12] Hughes, R. T., Zhu, L., & Bednarz, T. (2021). Generative adversarial networks–enabled human–artificial intelligence collaborative applications for creative and design industries: A systematic review of current approaches and trends. Frontiers in artificial intelligence, 4, 604234.
[13] Anuar, R., Abidin, S. Z., & Zakaria, W. Z. W. (2019). The design, development and evaluation of tpsack courseware to facilitate the art and design education students artistic skills knowledge. Asian Journal of University Education, 15(3), 69-82.
[14] Trach, Y. (2021). Artificial intelligence as a tool for creating and analysing works of art. Culture and arts in the modern world, 22, 164-173.
[15] Ha, A. Y. J., Passananti, J., Bhaskar, R., Shan, S., Southen, R., Zheng, H., & Zhao, B. Y. (2024, December). Organic or diffused: Can we distinguish human art from ai-generated images?. In Proceedings of the 2024 on ACM SIGSAC Conference on Computer and Communications Security (pp. 4822-4836).
[16] Qiang, S. U. N. (2025). Deep Learning-Based Modeling Methods in Personalized Education. Artificial Intelligence Education Studies, 1(1), 23-47.
[17] Zhang, T. (2025). Constructing and evaluating the effects of an immersive teaching mode for art education based on machine learning. Journal of Computational Methods in Sciences and Engineering, 14727978251322681.
[18] Cai, Q., Zhang, X., & Xie, W. (2023). Art Teaching Innovation Based on Computer Aided Design and Deep Learning Model. Computer-Aided Design and Applications, 124-139.
[19] Feng Xu,Kang Chen,Maosheng Zhong,Lei Liu,Huizhu Liu,Xianzeng Luo & Lang Zheng. (2024). DKVMN&MRI: A new deep knowledge tracing model based on DKVMN incorporating multi-relational information.. PloS one,19(10),e0312022.
[20] José ÂngeloFerreira,Edson LuizValmorbida,Bruno GoulartSato,Bruno PontesFuentes & RenanBotti. (2023). Forgetting curve models: A systematic review aimed at consolidating the main models and outlining possibilities for future research in production. Expert Systems,41(2),
[21] Changdong Yu,Xiaotong Gu,Yuhang Yao,Shihan Wang,Xiao Liang,Liuliu Pan & Yupeng Xiao. (2025). Real-time 6-DoF pose estimation for UUVs based on advanced CNN architecture with adaptive loss constraints. Ocean Engineering,333,121425-121425.