Student Online Learning Behavior Characteristics Based on Multidimensional Cognitive Model

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Abstract—Analysis of student learning behavior characteristics is an important means for educators to better understand students and improve the quality and effectiveness of teaching in the field of education. It is necessary to refer to students' cognitive levels for analysis of student learning behavior characteristics. However, existing algorithms only focus on the overall performance and grades of students, ignoring the individual differences in learning cognitive levels among students, which affects the accuracy of the analysis results. Therefore, this paper conducts research on student online learning behavior characteristics based on a multidimensional cognitive model. Firstly, a multidimensional and multilevel model for evaluating students' cognitive levels is constructed, and the process of evaluating students' cognitive levels is sustainable and can be adjusted in real-time as students' cognitive levels change. By considering the differences in evaluation levels and students' cognitive levels, targeted observation and extraction of students' online learning behavior characteristics can be achieved. A new model based on variational autoencoder neural network is proposed to perform decoupled representation of students' implicit preferences. By using a regularization term based on maximum mean difference, the model can learn independent hidden vectors sensitive to dynamic and static factors from students' online learning behavior history data and multidimensional cognitive evaluation history data. The experimental results verify the effectiveness of the constructed model.

Keywords—multidimensional cognitive model, cognitive level, online learning behavior, behavior feature representation

1 Introduction

The analysis of students' learning behavior characteristics is an important means for educators to better understand students and improve the quality and effectiveness of teaching [1–3]. Teachers can analyze students' learning characteristics by observing their classroom participation, questioning, group discussions, and other behaviors during classroom teaching. In personalized teaching, teachers can develop personalized teaching plans and resources for students based on their interests, learning habits, and ability differences, thereby improving students' learning interests and grades [4, 5]. Online learning platforms can analyze students' online learning behavior characteristics by collecting their learning data (such as login frequency, video viewing time, and completion of assignments), and provide more targeted teaching suggestions for educators [6–9].

Because students' cognitive levels directly affect their learning ability and effectiveness, it is necessary to refer to students' cognitive levels to analyze their learning behavior characteristics [10–13]. Teachers can design teaching content and methods suitable for students' cognitive levels, provide personalized learning resources and support for them, and help students set appropriate learning goals and implement more reasonable and effective learning behaviors to better understand and master knowledge [14–16].

Lai et al. [17] uses a comprehensive behavior prediction model to study the relationships between attitudes, subjective norms, self-efficacy, and behavioral intentions, as well as the relationships between intentions, convenience conditions, self-regulation skills, and the actual use of mobile technology in autonomous language learning. The study also examines whether self-regulation skills regulate intentions and actual use. The results show that students' self-regulation skills and intentions significantly predict their actual use of mobile technology. As self-regulation skills improve, the relationship between intention and actual behavior becomes stronger. Within the learning community, individuals have some similarities in terms of regularity of study time, demand for learning resources, and the need for guidance and companionship. Analyzing the differences and connections in the learning behavior of different groups can help generate more effective, targeted, and comprehensive learning decisions. However, existing research on analyzing the learning behavior of different types of learning groups is not extensive or in-depth enough. Therefore, Li et al. [18] attempts to explore a learning decision-making model based on the impact of group learning behavior. First, the traditional behavior tree model is improved using the advantages of Q-learning to construct a new model, which is used to study group learning behavior. Then, decision-making ideas are combined with game models, and a complex network structure is used to explore the evolutionary laws of group learning decisions based on multiple games. Finally, the effectiveness of the constructed model is verified using experimental results.

Through the combing and summarizing of existing methods, it is known that the existing research on analyzing the characteristics of students' online learning behavior has not fully considered that students' learning behavior and needs may change over time, which may lead to outdated and inaccurate analysis results. Some algorithms only focus on students' overall performance and grades, ignoring the individual differences in students' cognitive levels in learning, thereby affecting the accuracy of analysis results. Therefore, this paper takes the news and propaganda course in vocational colleges as an example to conduct a study on students' online learning behavior characteristics based on a multi-dimensional cognitive model.

2 Construction of a multi-dimensional cognitive model

Assuming that there are t evaluation indicators for multi-dimensional cognitive assessment, that is, t response variables $b_1, b_2, \ldots, b_t$ representing students' cognitive reactions, repeated evaluations are conducted using B_{ipl} to represent the evaluation values of students' cognitive reactions. Here, $i = 1,2, \dots ,M$ represents the students, $p = 1,2, \dots ,Pi$ represents the pth evaluation of student i, P represents the total number of evaluations for student i, and $l = 1,2, \dots ,t$ represents the lth cognitive reaction variable. For each student's cognitive reaction variable b_i $(i = 1,2, \dots ,M)$, a dummy variable $C_i(i = 1,2, \dots ,t)$ is defined. If the evaluation of cognitive reaction variable bi belongs to the ith student, then $C_i = 1$, otherwise $C_i = 0$. Assuming that different students' cognitive reaction variables have the same growth trend, the intercept corresponding to the lth cognitive reaction variable of the ith student is represented by γ_{1pl}, the slope corresponding to the pth evaluation of the lth cognitive reaction variable of the ith student is represented by γ_{1pl}, and the residual corresponding to the lth cognitive reaction variable of the pth evaluation of the ith student is represented by o_{ipl}. Thus, the model expression is:

$$B_{ipl} = \sum_{l} C_l (\gamma_{0il} + \gamma_{1il} p + o_{ipl}) \tag{1}$$

Let the average intercept and slope of the lth student's cognitive reaction variable be represented by fixed parameters γ_{0l} and γ_{1l}, and let the random variables for the intercept and slope of the lth student's cognitive reaction variable be represented by random parameters v_{0il} and v_{1il}. Thus, we have:

$$\gamma_{0il} = \gamma_{0l} + v_{0il} \tag{2}$$

$$\gamma_{1il} = \gamma_{1l} + v_{1il} \tag{3}$$

Similar to the multi-level model with a single response variable, the residuals at each level of the student's cognitive reaction need to follow a normal distribution. Compared with the multi-level model with a single response variable, the constructed multi-dimensional and multi-level model can obtain an estimate of the covariance of the student's cognitive reaction variables, which is the main advantage of the multi-dimensional and multi-level model over the single response variable model.

Next, the construction steps of the model will be elaborated in detail:

Step 1: Establish an unconditional model to determine whether the variation of the student's cognitive reaction variables is zero without the addition of independent variables. First, define the corresponding student's cognitive reaction variables $B_{itl}(l = 1,2, \dots ,t)$ using dummy variables $C_i(i = 1,2, \dots ,t)$ and construct the first layer of the model. Assuming that different students' cognitive reaction variables have the same growth trend, the value and random variation of the lth intermediate cognitive reaction variable of the ith student in the pth evaluation in the second layer of the model are represented by ϕ_{ipl} and k_{ipl}, respectively. The following expression gives the first-layer expression of the model:

$$B_{ipl} = \phi_{ipl} C_i + k_{ipl} \tag{4}$$

Assuming that the average value of the lth cognitive reaction variable of the ith student in P_i evaluations is represented by γ_{il0}, and the random variation in the second layer of the model is represented by o_l, the following expression gives the second-layer expression of the model:

$$\phi_{ip} = \gamma_{il0} + o_l \tag{5}$$

Assuming that the average value of the lth cognitive reaction variable in P_i evaluations for M students is represented by b_{l00}, and the random variation is represented by v_{l0}, the following expression gives the second-layer expression of the model:

$$\gamma_{ip0} = \alpha_{l00} + v_{l0} \tag{6}$$

Step 2: Build the complete model.

First, construct the first-layer model, which is the same as the construction process of the first layer of the unconditional model, to describe the multi-dimensional structure of the student's cognitive reaction variables:

$$B_{ipl} = \phi_{ipl} C_i + k_{ipl} \tag{7}$$

Assuming that the intercept corresponding to the lth cognitive reaction variable of the ith student is represented by γ_{il0}, the slope corresponding to the lth cognitive reaction variable of the ith student is represented by γ_{il1}, and the random variation in the second layer of the model is represented by o_l. The following expression gives the second-layer expression of the model incorporating the independent variable p that describes repeated evaluations:

$$\phi_{ipl} = \gamma_{il0} + \gamma_{il1} p + o_l \tag{8}$$

Assuming that the value of the evaluation index of the jth cognitive evaluation of the ith student is represented by the independent variable $Q_{ij}(j = 1,2, \ldots ,n)$, the influence of M students' Q_{ij} on the γ_{il0} of the second-layer model is represented by $\alpha_{l0j}(j = 1,2, \ldots ,n)$, with an intercept of α_{l00} and random variation represented by v_{l0}. The slope of the lth cognitive reaction variable in P_i evaluations for M students is represented by α_{l10}, and the impact of the independent variable Q_{ij} on the γ_{il1} of the second-layer model is represented by $\alpha_{l1j}(j = 1,2, \ldots ,n)$, with random variation represented by v_{l1}. The following expression gives the third-layer expression of the model incorporating independent variables $Q_{ij}(j = 1,2, \ldots ,n)$ to describe the cognitive evaluation index:

$$\gamma_{il0} = \alpha_{l00} + \alpha_{l01}(Q_{i1}) + \alpha_{l02}(Q_{i2}) \cdots + \alpha_{l0n}(Q_{in}) + v_{l0} \tag{9}$$

$$\gamma_{il1} = \alpha_{l10} + \alpha_{l11}(Q_{i1}) + \alpha_{l12}(Q_{i2}) \cdots + \alpha_{l1n}(Q_{in}) + v_{l1} \tag{10}$$

3 The extraction of implicit preferences of students' online learning behavior

In order to effectively learn students' implicit preferences from their online learning behavior historical data and provide educators with a more comprehensive and accurate student profile, this paper refers to the output evaluation results of the constructed multi-dimensional and multi-level model applied to student's multi-dimensional cognitive evaluation, and proposes a new model based on variational autoencoder neural network for decoupled representation of student's implicit preferences. By using a regularization term based on maximum mean discrepancy, the model can learn independent latent vectors that are sensitive to dynamic and static factors from both the historical data of students' online learning behavior and multi-dimensional cognitive evaluation, thereby improving the performance of the model.

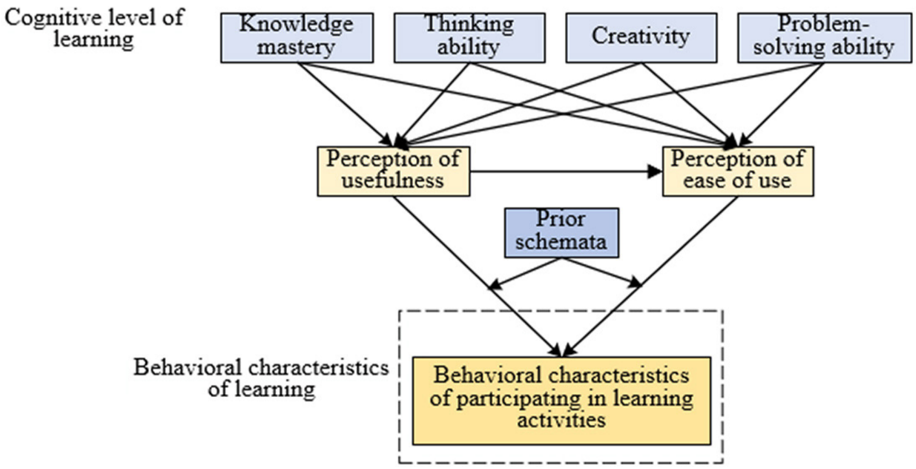

Fig. 1. Theoretical and hypothetical model of the influencing factors of students' implicit preferences in online learning behavior

This chapter refers to the representation theory, technology acceptance model, and schema theory, and constructs a theoretical and hypothetical model of the influencing factors of students' implicit preferences in online learning behavior, as shown in Figure 1. The stimulus factors include the student's cognitive level, which covers knowledge mastery, thinking ability, creativity, and problem-solving ability. The individual psychology represents the student's perception of the usefulness and ease of use of learning activities on the online learning platform, and the response is the online learning behavior generated by the student. Between the stimulus and response, the utility of online learning behavior is regulated by implicit preferences, that is, prior schemata, which are modulated by the student's perception of usefulness and ease of use.

Next, this paper will provide a detailed description of the decoupled variational inference process and specific implementation details of the proposed model.

3.1 Problem definition and inference process

Definition of the problem: Let the set of students λ contain $|\lambda|$ students, and the set of learning activities U contain $|U|$ learning activities. The preference matrix is $S\in \{0,1\}^{|\lambda|\times|U|}$, where an element $s_{v,i} = 1$ indicates that student v has interacted with learning activity i, and $s_{v,i} = 0$ indicates that there is no interaction. Given a student v, define

$U_u = \{i \in U | s_{v,i} = 1\}$, $P = |U|$, and U_v contains all learning activities that have interacted with student v. At the same time, a time label $C \in S^{|\lambda| \times |U|}$ is added to S, where $c_{v,i}$ represents the time when student v interacts with learning activity i, and $c_{v,i}$ is empty when $s_{v,i} = 0$. Let $a_{v,p}(1 \leq p \leq P)$ represent the p-th item in U_v arranged according to the order of $c_{v,i}$, and a_v represent the interaction sequence $\{a_{v,1}, a_{v,2}, \ldots, a_{v,P}\}$ between student $v \in V$ and the learning activities. The model is designed to use a_v to learn the decoupling representation $c_{v,p} = [c_v^d c_{m,p}^n]$ and the decoder based on the latent vector $c_{v,p}$ to reconstruct the student behavior $a_{v,p}^*$. It should be noted that the latent vector $c_{v,p}^n$ is related to the time step p, while the latent vector c_v^d is independent of the time step p.

Given a combination sequence a_v of a student's online learning behavior historical data and multi-dimensional cognitive evaluation historical data, let $c_{vp} = [c_{v,}^d c_{v,p}^n]$ be the decoupled representation of the student's online learning behavior, and the goal of the model constructed in this paper is to learn the representation $Cv = \{c_{v,1}, \ldots, c_{v,P}\}$ composed of c_{vp}. In ideal cases, the time-invariant latent variable of the student can be modeled by capturing the global aspect of the sequence a_v and represented by c_v^d, while the time-variant latent variable of the student v can be modeled by $c_{v,p}^n$. Assuming that c_v^d, $c_{v,p}^n$ follow a distribution t, the following probability generation model can be given:

$$t(a_v, c_v) = \prod_{p=1}^{P} t(c_v, p) t\omega(a_{v,p} \mid c_{v,p}) \tag{11}$$

Assuming that c_v^d and $c_{v,p}^n$ are mutually independent, i.e., $t(c_{v,p}) = t(c_v^d)t(c_{v,p}^n)$, then the above equation can be modified as follows:

$$t(a_v, c_v) = t(c_v^d) \prod_{t=1}^{P} t(c_{v,p}^n) t\omega(a_{v,p} \mid c_{v,p}) \tag{12}$$

In order to extract valuable information from the hidden variable c_v that can be hidden behind a_v in advance, c_v^d and $c_{v,p}^n$ can be sampled from the approximate posterior distribution $w_\Phi(c_v^d|a_v)$ and $w_\psi(c_{v,p}^n|a_{v,[1:p]})$. ($c_v^d \sim w_\Phi(c_v^d|a_v)$, $w_\Psi(c_{v,p}^n|a_{v,[1:p]})$). Assuming that the divergence between the approximate posterior distribution w of the random variable and the prior distribution t is represented by C, a variational lower bound $\Sigma a_v log_t(a_v)$ can be obtained:

$$\sum_{a_v} \log t(a_v) \geq \sum_{a_v} \begin{bmatrix} O_{w_\Phi} \sum_{p=1}^{P} O_{w_\Psi(c_{v,p}^n | a_{v,[1:p]})} \left(\log t_\omega(a_{v,p+1}) \right) - C\left(w_\Phi(c_v^d \mid a_v) \,\|\, t(c_v^d) \right) \\ -\sum_{p=1}^{P} C\left(w_\Psi(c_{v,p}^n \mid a_{v,[1:p]}) \,\|\, t(c_{v,p}^n) \right) \end{bmatrix} \tag{13}$$

The parameters of the two encoder networks are represented by Φ and Ψ. This paper uses two encoders W_Φ and W_Ψ to implement the two approximate posteriors in the above equation. It can be regarded that each learning activity is encoded as a c-dimensional vector representation, and the embedding representation of the learning activity set U can be denoted as $U \in S^{|u| \times c}$. In the embedding space, the combination sequence a_v can be represented by a high-dimensional sequence $A_{v,[1:P]} = \{A_{v,1}, \ldots, A_{v,P}\}$. By inputting $a_{v}, _{[1:P]}$ to W_Φ and W_Ψ, the latent variable c_v can be inferred in the embedding space. Let the parameters of the decoder network be represented by ω, and the final decoder T_ω will reconstruct a_v. The training mode of the model is characterized by the following equation:

$$\max_{\Phi,\Psi,\omega,U} \sum_{a_v} \left[\begin{array}{l} O_{W_\Phi(c_v^d|a_v)} \sum_{p=1}^{P} O_{W_\Psi(c_v^n|a_v)} \left(\log T_\omega(a_{v,p} \mid c_{v,p}) \right) - \gamma_1 C\left(W_\Phi(c_v^d \mid a_v) \parallel T(c_v^d) \right) \\ -\gamma_2 \sum_{p=1}^{P} C\left(W_\Psi(c_{v,p}^n \mid a_{v,[1:p]}) \parallel T(c_{v,p}^n) \right) \end{array} \right] \tag{14}$$

The model constructed outputs the predicted preference of the student $a^*_{v,p}$ at time step p, that is, the learning activities that the student may interact with from time step p to $p + L$. Here, L represents the number of learning activities that the model needs to predict for the student after time step p, and it can be freely set. In order to make the prediction more accurate, it is necessary to minimize the difference between $a^*_{v,p}$ and the true student behavior.

3.2 Model architecture

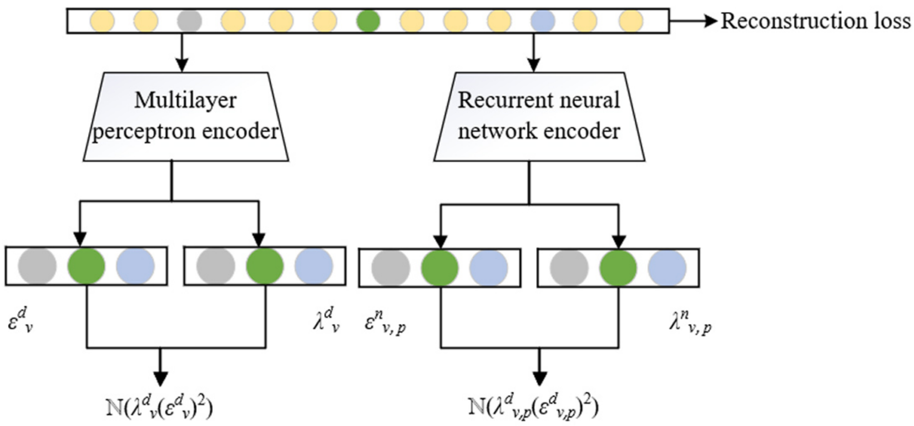

Fig. 2. Encoder structure

The constructed model is divided into three parts: encoder, sampling, and decoder. Figure 2 shows the encoder structure. Since the model needs to take derivatives of the parameters of random variables during training, but the sampling operation of the combination sequence is not differentiable, a reparameterization technique needs to be introduced to ensure that the model can backpropagate. In order to capture the invariant features of learning activities in the student's online learning behavior sequence, a multilayer perceptron encoder W_Φ is used to extract the global relationship in the entire sequence, and the mean λ_v^d and standard deviation ε_v^d of the distribution corresponding to the student's online learning behavior can be obtained. Furthermore, through the reparameterization technique, c_v^d follows the distribution $N(\lambda_v^d(\varepsilon_v^d)^2)$, and the following expression gives the process:

$$\begin{aligned} \lambda_v^d, \ln \varepsilon_v^d &= MLP(a_{v,[1:P]}) \\ c_v^d &= \lambda_v^d + \varepsilon_v^d \otimes \rho(\rho \sim M(0,I)) \end{aligned} \tag{15}$$

Assuming element multiplication is represented by ⊗. In order to capture the temporal information of learning activities in the student's online learning behavior sequence, this paper constructs an encoder based on the recurrent neural network to model $W_\psi(c^n_{v,[1:P]}|a_v)$. The output $f_{v,p}$ of the GRU unit in the recurrent neural network contains the information of $a_{v,[1:P]}$ at time steps 1 to p. The Gaussian distribution of the student's dynamic preference is represented by $W_\psi\,(c^n_{v,[1:P]}|a_{v,[1:p]})$, and the mean $\lambda^n_{v,p}$ and standard deviation $\varepsilon^n_{v,p}$ are obtained by inputting $f_{v,p}$ into a fully connected layer. Similarly, through the reparameterization technique, $c^d_{v,p}$ follows the distribution $N(\lambda^d_{v,p}(\varepsilon^d_{v,p})^2)$, and the process expression is as follows:

$$\begin{aligned} f_{v,p} &= GRU(a_{v,p}, f_{v,p-1}) \\ \lambda^n_{v,p}, \ln \varepsilon^n_{v,p} &= MLP(f_{v,p}) \\ c^n_{v,p} &= \lambda^n_{v,p} + \varepsilon^n_{v,p} \otimes \rho(\rho \sim M(0,I)) \end{aligned} \tag{16}$$

After obtaining the hidden vectors c_v^d and $c^n_{v,p}$ of two different student online learning behavior preferences through the encoder, they are concatenated as $c_{v,p} = [c_v^d, c^n_{v,p}]$, and the concatenated result is input into the decoder. Figure 3 shows the sampling process, and Figure 4 shows the decoder structure. For each learning activity $i \in U$, a target learning activity embedding hi is defined, and the cosine similarity between $c_{v,p}$ and h_i is calculated as the recommendation score r_i for all learning activities:

$$r_i = \frac{1}{\varsigma} \frac{c^P_{v,p} h_i}{\| c_{v,p} \| 2 \| h_i \| 2} \tag{17}$$

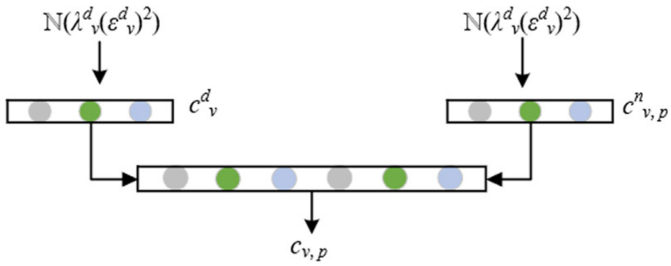

Fig. 3. Sampling process

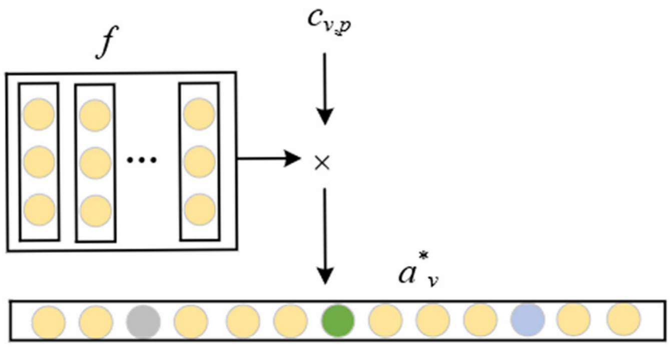

Fig. 4. Decoder structure

Let ς represent the constraint of similarity scores r_i between $[-1/\varsigma, 1/\varsigma]$. By performing a *softmax* operation on the scores of all learning activities, the reconstructed student behavior distribution $T_\omega(A_p|C_p)$ parameterized by ω is obtained, which is the predicted student behavior a_p^X at each time step.

$$T_\omega(a_{v,p} \mid c_{v,p}) = soft\max\left(\{r_1; r_2; \ldots; r_{|U|}\}\right) \tag{18}$$

3.3 Maximum mean discrepancy (MMD)

In order to minimize the difference between the prior probability distribution and the posterior probability distribution, this paper introduces Maximum Mean Discrepancy (*MMD*), which calculates the difference between the two by mapping the prior and posterior probability distributions into a Hilbert space and minimizing the distance between them. Assuming that the length of the student behavior sequence is represented by P, the instance from T is represented by $\hat{c}$, the instance from W is represented by c, and the Gaussian kernel function is represented by $l(a,b) = exp(-\|a-b\|^2/2)$. Since c_v^d is independent of time step p, the *MMD* between the prior distribution and the posterior distribution of c_v^d and $c_{v,p}^n$ can be represented by the following formula when $P = k$.

$$\begin{aligned} C\left(W_\phi(c_v^d \mid a_v) \,\|\, T(c_v^d)\right) &= MMD\left(W_\phi(c_v^d \mid a_v) \,\|\, P(z_u^c)\right) \\ C\left(W_\Psi(c_{v,p}^n \mid a_{v,[1:p]}) \,\|\, T(c_{v,p}^n)\right) &= MMD\left(W_\Psi(c_{v,p}^n \mid a_{v,[1:p]}) \,\|\, T(c_{v,p}^n)\right) \end{aligned} \tag{19}$$

$$\begin{aligned} MMD_\Psi\left(W_\Psi(c_p^n) \,\|\, T(c_p^n)\right) &= \frac{1}{P(P-1)} \sum_{i \neq j}^{P} l(c_{v,i}^n, c_{v,j}^n) \\ &+ \frac{1}{P(P-1)} \sum_{i \neq j}^{P} l(\hat{c}_{v,i}^n, \hat{c}_{v,j}^n) - \frac{2}{P^2} \sum_{i,j}^{P} l(\hat{c}_{v,i}^n, \hat{c}_{v,j}^n) \end{aligned} \tag{20}$$

$$MMD\left(W_\phi(c_v^d \mid a_{v,[1:p]}) \,\|\, T(c_v^d)\right) = -2l(c_{v,i}^d, \hat{c}_{v,j}^d) \tag{21}$$

$$\max_{\phi,\psi,\Psi,U}\sum_{a_v}[O_{W_\Psi(c_v^d|a_v)}\sum_{p=1}^{P}O_{W_\Psi}(c_{v,i}^n|a_v)\left(\log T_\omega(a_{v,p},c_{v,p})\right)-\gamma_1\sum_{p=1}^{P}\left(\frac{1}{P(P-1)}\sum_{i\neq j}^{P}l(c_{v,i}^n,c_{v,j}^n)+\frac{1}{P(P-1)}\sum_{i\neq j}^{P}l(\hat{c}_{v,i}^n,\hat{c}_{v,j}^n)\right)-\frac{2}{P^2}\sum_{i,j}^{P}l(\hat{c}_{v,i}^n,c_{v,j}^n)-\gamma_2\left(-2l(c_{v,i}^d,\hat{c}_{v,j}^d)\right)] \tag{22}$$

Figure 5 shows a schematic diagram of the Maximum Mean Discrepancy (MMD) loss.

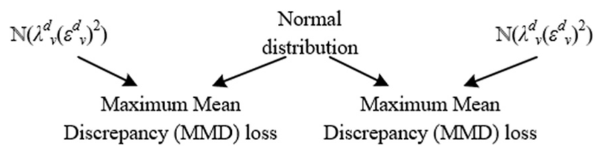

Fig. 5. A schematic diagram of the maximum mean discrepancy (MMD) loss

4 Experimental results and analysis

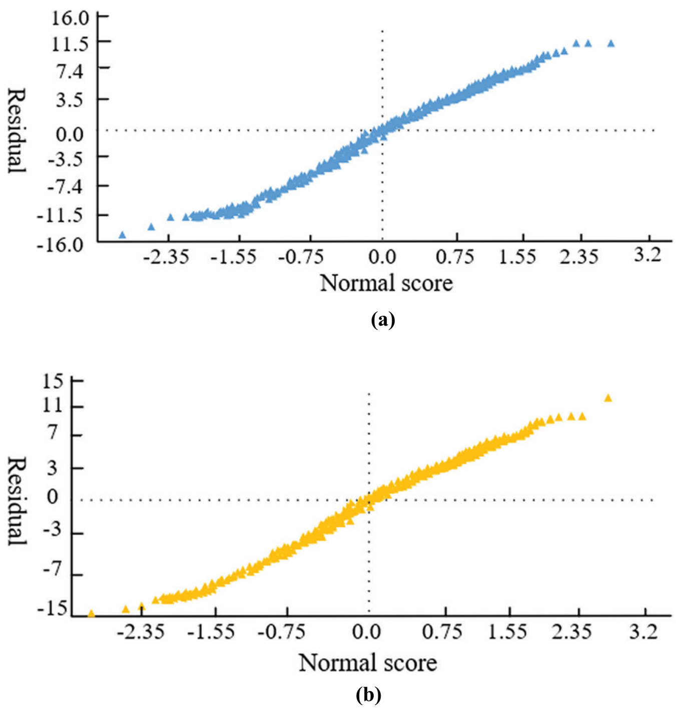

Fig. 6. Distribution of residuals at different time points (measurement units)

Studying the characteristics of student online learning behavior based on the multi-dimensional cognitive model is of great significance. By delving into the online learning behavior and cognitive characteristics of students, useful guidance and suggestions can be provided for vocational education news and propaganda courses. Taking the vocational news and propaganda course as an example, this paper evaluates the residual situation of each cognitive level of students under different normal scores, and draws the distribution of residuals as shown in Figure 6. As can be seen from the figure, the residual distribution is close to a straight line, indicating that the normal distribution assumption of the residual for different cognitive levels is reasonable. Table 1 presents the results of one-way analysis of the four evaluation indicators of knowledge mastery, thinking ability, creativity, and problem-solving ability.

Table 1. One-way analysis results of evaluation indicators, presented as X±S

Activity Forms	Participation	X±S			
		Knowledge Mastery	Thinking Ability	Creativity	Problem-Solving Ability
Video courses	Never	17.41±4.76	15.25±8.41	19.41±5.11	28.44±4.41
	Occasionally	21.01±5.33	12.41±3.74	16.02±4.61	31.11±5.00
	Frequently	22.34±4.33	12.05±5.44	15.46±4.06	28.51±6.31
Interactive courses	Never	21.55±4.97	12.95±5.61	15.52±4.08	29.19±4.81
	Frequently	20.71±4.83	11.31±6.41	17.56±8.88	28.46±8.21
Live courses	Never	21.55±4.97	12.95±5.61	15.52±4.08	29.19±5.81
	Frequently	20.71±5.83	11.31±4.41	17.56±6.88	28.46±4.21
Group discussions	Never	21.55±4.97	12.95±5.61	15.52±5.08	29.19±6.81
	Frequently	20.71±3.83	11.31±5.41	17.56±7.88	28.46±7.21
Self-evaluation and testing	Never	21.06±5.21	9.01±4.44	15.61±4.01	29.51±7.74
	Occasionally	21.31±5.37	12.56±6.31	15.54±8.51	30.01±5.44
	Frequently	21.56±5.66	13.87±5.40	16.74±6.37	27.31±6.34
Projects and assignments	Never	21.84±5.01	14.41±5.20	16.74±7.64	29.91±5.55
	Frequently	20.61±4.55	10.88±5.91	15.61±3.54	28.21±6.21
Personalized learning paths	Never	21.26±4.54	12.84±6.31	16.21±5.01	28.01±6.41
	Frequently	21.51±5.31	11.85±5.64	15.99±7.01	30.31±5.01

Online open courses offer several typical learning activity forms, such as video courses, interactive courses, live courses, group discussions, self-evaluation and testing, projects and assignments, and personalized learning paths. As shown in the table above, for video courses, students who frequently participate perform better in knowledge mastery, while those who occasionally participate perform better in thinking ability, creativity, and problem-solving ability. In terms of interactive courses and live courses, there is no significant difference in performance between students who never participate and those who frequently participate in all four dimensions. For group discussions, students who never participate perform better in thinking ability and problem-solving ability, with no significant difference in other dimensions. For self-evaluation and testing, students who frequently participate perform better in knowledge mastery, thinking ability, and creativity, while those who occasionally participate perform better in problem-solving ability. Students who never participate in projects and assignments perform better in knowledge mastery and thinking ability, with no significant difference in other dimensions. In terms of personalized learning paths, there is no significant difference in performance between students who never participate and those who frequently participate in all four dimensions. In summary, different activity forms have different effects on students in each dimension. Therefore, appropriate learning activity forms should be selected based on the specific cognitive level of students, that is, different forms of learning behavior should be implemented.

Table 2. Comparison of experimental results

Model	***NDCG***		***Recall***		***Precision***	
	@5	**@50**	**@5**	**@50**	**@5**	**@50**
RNN	9.34	19.55	6.59	36.12	8.41	5.46
LSTM	9.78	21.41	7.41	39.78	8.63	5.71
GRU4Rec	19.51	31.41	14.23	51.21	15.81	7.41
ST-GCN	19.87	31.94	14.23	51.56	16.54	7.33
The model proposed in this paper	20.49	32.91	14.65	53.64	16.91	7.61

Table 2 shows the performance of different models on two metrics (normalized discounted cumulative gain *NDCG* and *Recall* and *Precision*) on these metrics, where @5 and @50 represent the evaluation at the top 5 and top 50 results of the extracted implicit preferences of online learning behaviors of students. The five participating models include *RNN*, *LSTM*, *GRU4Rec*, *ST-GCN*, and the model proposed in this paper. From the table, it can be seen that the model proposed in this paper performs the best on *NDCG*@5 and *NDCG*@50, reaching 20.49 and 32.91, respectively. The second-best is *ST-GCN*, with scores of 19.87 and 31.94, respectively. RNN and LSTM perform relatively poorly on these two metrics. On *Recall*@5 and *Recall*@50, the model proposed in this paper also performs the best, reaching 14.65 and 53.64, respectively. The performances of *GRU4Rec* and *ST-GCN* are relatively good, but slightly inferior to the model proposed in this paper on these two metrics. The performances of *RNN* and *LSTM* are relatively poor. On *Precision*@5 and *Precision*@50, the model proposed in this paper still performs the best, with scores of 16.91 and 7.61, respectively. The second-best is *ST-GCN*, with scores of 16.54 and 7.33, respectively. *RNN* and *LSTM* also perform poorly on these two metrics. Overall, the model proposed in this paper performs the best on these metrics, indicating that it has better performance in extracting implicit preferences of online learning behaviors of students and has more advantages than other models.

To analyze the effect of the length of historical learning behavior on the performance of the constructed model, a comparison experiment was conducted, and the NDCG@50 values were obtained as shown in Tables 3 and 4. Table 3 shows the performance of students with different lengths of historical learning behavior under three models (*GRU4Rec*, *ST-GCN*, and the model proposed in this paper). The data shows that there are differences in the performance of the models under different lengths of historical learning behavior. When the length is between 1 and 10, *GRU4Rec* performs the best, followed by the model proposed in this paper, and *ST-GCN* performs the worst. When the length is between 11 and 20, the model proposed in this paper and *ST-GCN* perform similarly, and both are better than *GRU4Rec*. When the length is between 21 and 50, 51–100, 151–200, 201–300, and over 301, the model proposed in this paper performs the best, followed by *ST-GCN*, and *GRU4Rec* performs the worst. When the length is between 51 and 100, the model proposed in this paper performs the best, followed by *ST-GCN*, and *GRU4Rec* performs the worst. When the length is between 101–150, *ST-GCN* performs the best, followed by the model proposed in this paper, and *GRU4Rec* performs the worst. The results shown in Table 4 are similar. Overall, the performance of the model proposed in this paper is better than the other two models in most historical learning behavior length intervals. In practical applications, appropriate models can be selected based on the historical learning behavior length of students.

Table 3. The effect of the length of historical learning behavior sequences in sample set 1 on *NDCG*@50 (%)

The Length of Historical Student Learning Behavior Sequences	*GRU4Rec*	*ST-GCN*	The Model Proposed in this Paper
[1–10]	14.31	6.14	7.29
[11–20]	21.11	24.41	24.97
[21–50]	24.34	35.61	36.61
[51–100]	19.55	32.33	33.01
[101–150]	21.64	32.21	31.51
[151–200]	21.41	26.14	27.22
[201–300]	18.49	26.23	27.21
[301–]	18.55	21.31	26.81

Table 4. The effect of the length of historical learning behavior sequences in sample set 2 on *NDCG*@50 (%)

The Length of Historical Student Learning Behavior Sequences	*GRU4Rec*	*ST-GCN*	The Model Proposed in this Paper
[1–10]	2.71	3.51	7.05
[11–20]	3.57	3.01	8.05
[21–50]	7.44	6.17	10.66
[51–100]	7.31	4.81	12.26
[101–150]	1.12	6.77	10.25
[151–200]	1.61	7.41	9.74
[201–300]	1.62	7.02	8.81
[301–]	–	–	–

Figure 7 shows the causal experimental results before and after introducing Maximum Mean Discrepancy (*MMD*). It can be seen that after introducing *MMD*, the performance of the model has improved on all evaluation metrics. The *NDCG@5* score increased from 19.81 to 20.61, *NDCG@*50 increased from 32.21 to 32.88, *Recall@*5 increased from 14.08 to 14.71, *Recall@*50 increased from 52.51 to 53.74, *Precision@*5 increased from 16.33 to 16.91, and *Precision@*50 increased from 7.58 to 7.61. By using *MMD* as a regularization term instead of *KL* divergence, the performance of the model has been improved on all evaluation metrics. This indicates that *MMD* is more suitable for measuring the difference between two different but related distributions and makes the latent vectors close to their prior distribution. This improvement helps to enhance the generative ability of the latent vectors and the expressive power of the model, resulting in better performance on evaluation metrics such as *NDCG*, Recall, and Precision. In summary, using *MMD* as a regularization term has advantages over *KL* divergence in measuring distribution differences, improving model expressive power and generative ability. This advantage is reflected in the improvement of the model's performance on all evaluation metrics, providing better performance for the practical application of extracting implicit preferences of online learning behaviors of students.

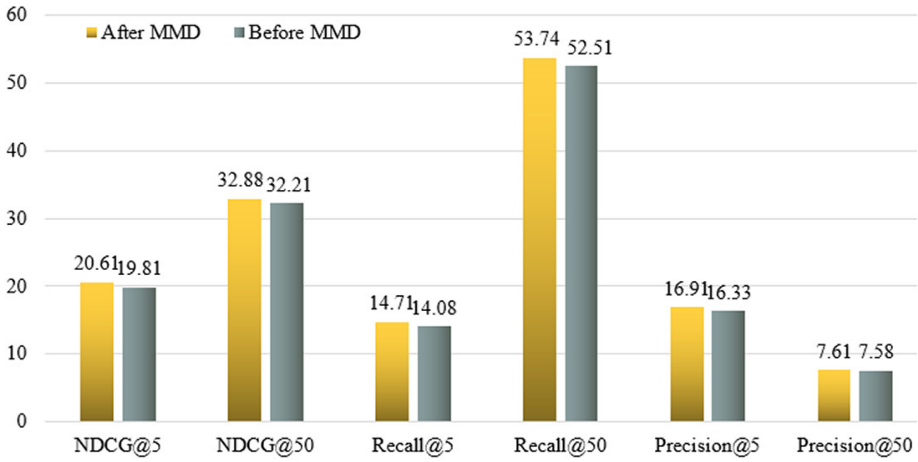

Fig. 7. Causal experimental results before and after introducing MMD

5 Conclusion

This paper conducts a study on the characteristics of student online learning behavior based on the multi-dimensional cognitive model. Firstly, a multi-dimensional and multi-level model is constructed for the evaluation of students' multi-dimensional cognitive levels, which has sustainability and can be adjusted in real-time as students' cognitive levels change. By considering the differences in evaluation levels and students' cognitive levels, targeted observation and extraction of student online learning behavior characteristics can be achieved. A new model based on Variational Autoencoder Neural Network is proposed for decoupling representation of student implicit preferences.

By using Maximum Mean Discrepancy as a regularization term, the model can learn independent latent vectors that are sensitive to dynamic and static factors from both the historical data of student online learning behavior and the multi-dimensional cognitive evaluation history data. Residual distribution graphs are drawn based on the evaluation residuals of different cognitive levels of students under different normal scores. Single-factor analysis results of the four-dimensional evaluation metrics of knowledge mastery, thinking ability, creativity, and problem-solving ability are presented. The performance of different models on two metrics (Normalized Discounted Cumulative Gain (*NDCG*) and recall and precision) is demonstrated. The experimental results show that the proposed model has better performance in extracting implicit preferences of student online learning behavior and has advantages over other models. To analyze the effect of the length of the historical learning behavior sequence on the performance of the constructed model, a comparison experiment is conducted, and the *NDCG@*50 values for different lengths of the historical learning behavior sequence are obtained. Overall, the performance of the proposed model is better than the other two comparison models in most historical learning behavior length intervals. In practical applications, a suitable model can be selected according to the length of the student's historical learning behavior. The causal experimental results before and after introducing Maximum Mean Discrepancy (*MMD*) are presented to validate the scientific and effective introduction of *MMD*.

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