Prediction Model of Students' Learning Motivation Based on Combinatorial Optimization Algorithm

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Abstract—The strength of college students' learning enthusiasm directly affects their learning effect. Studying and predicting students' learning enthusiasm has positive significance for improving college students themselves and college education. Existing methods have not involved how to select and extract features related to students' learning enthusiasm, so it is difficult to meet the needs of learning enthusiasm prediction. Therefore, this article takes English learning as an example to conduct a research on the prediction model of students' learning enthusiasm based on combinatorial optimization algorithm. Taking English learning as an example, this article expounds in detail the main manifestations of students' learning enthusiasm, and predicts the intention of students to participate in learning behaviors based on the enumerated behaviors, so as to judge students' learning enthusiasm, and gives the construction method of the prediction model. This study constructs a network model for the evaluation of students' learning autonomy, and finally outputs the grade results of students' learning autonomy evaluation. Based on the obtained predictions of students' participation in learning behavior intentions and the evaluation results of students' learning autonomy, a combined model is established through the weighting of the inverted error method to predict the regression of students' learning enthusiasm. Experimental results verify the effectiveness of the constructed single model and combined model.

Keywords—combinatorial optimization, learning behavior intention prediction, learning autonomy evaluation, learning motivation analysis

1 Introduction

College students' learning enthusiasm is the attitude of active participation, active exploration and continuous engagement shown by college students in the learning process, and it is the internal motivation that directly promotes their learning [1–5]. Contemporary college students have a certain degree of autonomy in their learning activities, that's, they have the right and freedom to choose independently in terms of learning content, learning methods and learning time [6–11]. Although college students also need the guidance and management of teachers in learning, their knowledge structure has changed from the vertical accumulation in the middle school stage to the horizontal expansion in the university stage [12–19]. A college student who is active in learning has more clear goals and enthusiasm for learning in terms of class participation, independent learning, and seeking knowledge, and their academic performance and comprehensive quality are also higher.

Because the strength of college students' learning enthusiasm directly affects their learning effects, improving college students' learning enthusiasm will mean the improvement of teaching quality and the use efficiency of educational resources, and is also very obvious in the promotion of students' all-round development [20–22]. Therefore, studying and predicting students' learning enthusiasm has positive significance for improving college students themselves and college education.

Wang [23] conducted a questionnaire survey on 491 undergraduates of Wuhan Technology and Business University, focusing on three aspects: the current status of learning, the motivation that affects active learning, and the learning environment that students hope for. Using such empirical methods as literature analysis, questionnaire survey and participation in professional seminars, this article discusses the current situation of college students' learning enthusiasm and analyzes the motivations that affect learning initiative. The survey results show that there are obvious differences in the learning enthusiasm of college students in subjects and grades, so it is not enough to rely on a single force to improve students' learning initiative. Finally, on the basis of the questionnaire analysis, it puts forward a series of methods to thoroughly improve students' learning enthusiasm, that's, some feasible suggestions from the perspectives of school administrators, teachers, students and parents.

Galishnikova et al. [18] is to provide evidence that the formation of students' cognitive positivity, as part of the development of a comprehensive personality in a foreign language, becomes a decisive factor in the training of competitive specialists. The article points out that even with a sufficiently high level of mental development, strong memory, reasoning logic, broad horizons, work ability, and perseverance, even with all these qualities, it is necessary to constantly stimulate students' interest in learning and make the knowledge they acquire meaningful and value-oriented. In this regard, student determination and initiative are particularly important. As such, it becomes a prerequisite for student development. Based on teaching experience, this article outlines the vehicles for the development of cognitive positivity and proposes that the structure of student positivity is the interconnectedness of teachability, creativity, and intelligence. It expounds the methods of improving the enthusiasm of college students in English learning, and emphasizes the exploration of methodology and the improvement of certain teaching methods, tools and means.

Existing evaluation and prediction methods mainly include data mining, machine learning and artificial intelligence technology to analyze students' behavior, achievement and other relevant data. However, it's difficult of existing methods to adapt to the learning motivation prediction needs of different subjects, different educational stages and different student groups, which may lead to over-fitting or under-fitting. At the same time, these methods have not discussed how to select and extract features related to students' learning enthusiasm, so it is difficult to meet the needs of learning enthusiasm prediction. To this end, this article takes English learning as an example, and conducts research on the prediction model of students' learning enthusiasm based on combinatorial optimization algorithms. In the second chapter, taking English learning as an example, the article elaborates the main manifestations of students' learning enthusiasm in detail, and predicts the intention of students to participate in learning behaviors based on the enumerated behaviors, so as to judge students' learning enthusiasm, and gives the construction method of the prediction model. In the third chapter, the article constructs a network model for the evaluation of students' learning autonomy. The network model consists of a spatial self-attention module and a polarity detection branch. It uses the category labels of students' learning autonomy to guide the learning of evaluation tasks, and finally outputs the results of students' learning autonomy evaluation grades. In the fourth chapter, based on the prediction of students' participation in learning behavior intention and the evaluation results of students' learning autonomy, the article uses the inverted error method to weight and establish a combined model to conduct the regression prediction of students' learning enthusiasm. Experimental results verify the effectiveness of the constructed single model and combined model.

2 Prediction of students' participation in learning behavior intention

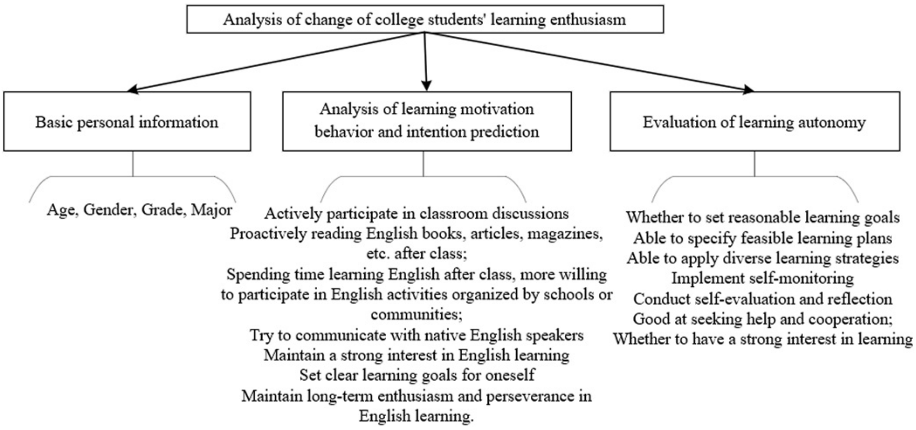

Fig. 1. Structure of the analysis method for the change of college students' learning enthusiasm

Figure 1 shows the structure of the analysis method for the change of college students' learning enthusiasm applied in this article. The key steps in the analysis of college students' learning enthusiasm herein are behavior analysis and intention prediction, and learning autonomy evaluation. Taking English learning as an example, students' learning enthusiasm is mainly manifested in the following aspects of behavior:

(1) Actively participate in classroom discussions and are eager to answer and ask questions;
(2) Actively read English books, articles, magazines, etc. after class to broaden vocabulary and improve reading comprehension;

(3) Spend time learning English after class, such as memorizing words, doing exercises, and practicing oral English, actively search for learning resources, and make plans for their own learning;
(4) More willing to participate in English activities organized by schools or communities, such as English corners, speech contests and English drama performances;
(5) Attempt to communicate with native English speakers to improve oral skills and cultural understanding. For example, make friends with international students, participate in language exchange activities, etc.;
(6) Use English in daily life, such as writing a diary, and writing a story or poetry in English, to improve writing and expression skills;
(7) Maintain a strong interest in English learning, and pay attention to the culture, history, society and other aspects of English-speaking countries to broaden their knowledge;
(8) Set clear learning goals for themselves, such as passing an English test or reaching a specific language level, and make plans to achieve these goals;
(9) Maintain long-term enthusiasm and perseverance in English learning, and never give up even in the face of difficulties and setbacks.

Predicting the behavior intentions of the above aspects can be more effective in judging students' learning enthusiasm.

Figure 2 shows the execution flow of the intention prediction model of students' participation in learning behavior constructed herein. This article first learns the historical interaction behavior sequence of students with timestamp information, and the module used is an improved time-aware *LSTM* module. Then, a multi-intent self-attention module is introduced to model the complex intentions of students in an interactive learning behavior. By introducing the unique feature information of students into the learning of the model to meet the personalized requirements of their behavioral intentions. The module can simultaneously extract the short-term and long-term dependencies of students' historical interactive behavior, which is more suitable for the intention prediction of students' participation in learning behaviors for judging students' learning enthusiasm. Figure 3 shows the architecture of an iterative unit module of the constructed prediction model.

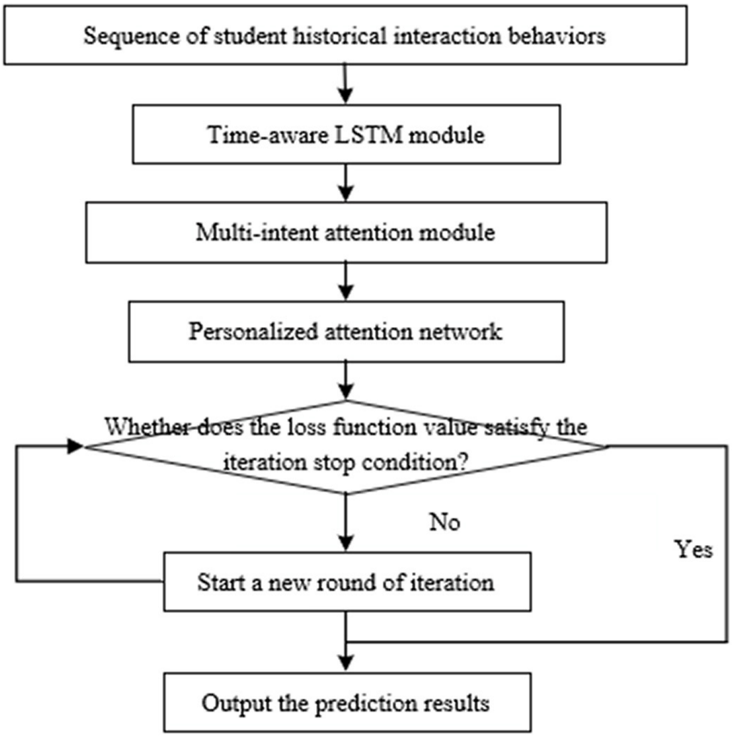

Fig. 2. Execution process of students' participation in learning behavior intention prediction model

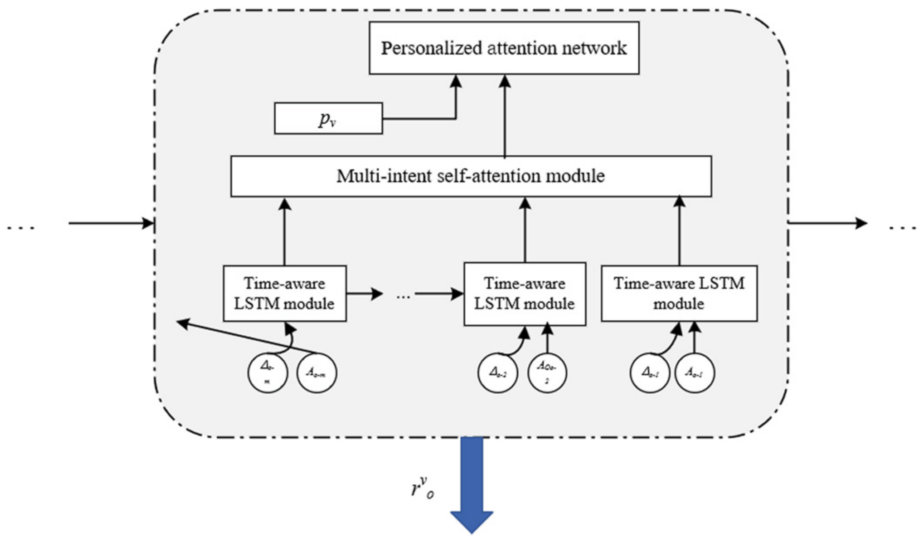

Fig. 3. Iterative unit module architecture

The proposed *LSTM* module adds a time interval variable, and the calculation formula of the forget gate of the module needs to be updated again. It's assumed that the input gate, forget gate and output gate of the *o*-th object are represented by i_o, g_o and t_o respectively. Cell activation status is represented by d_o. The input feature vector and hidden output are represented by a_o and f_o, respectively. The weight parameter is represented by $Q^{\{1,2,3\}}_{\{i,g,t,d\}}$ and the corresponding bias is represented by $y_{\{i,g,t,d\}}$, the time interval between a_{o-1} and a_o is represented by Δo, and the detailed formula of the module is represented by:

$$\begin{aligned}
i_o &= \varepsilon(Q_i^1 a_o + Q_i^2 f_{o-1} + y_i)\\
g_o &= \varepsilon(Q_g^1 a_o + Q_g^2 f_{o-1} + Q_g^3 \Delta_o + y_g)\\
t_o &= \varepsilon(Q_t^1 a_o + Q_t^2 f_{o-1} + y_t)\\
d_o &= g_o * d_{o-1} + i_o * \tanh(Q_d^1 a_o + Q_d^2 f_{o-1} + y_d)\\
f_o &= t_o * \tanh(d_o)
\end{aligned} \tag{1}$$

In order to obtain a higher-order intention representation of student participation learning behavior, f_o is next passed to the multi-intent self-attention module. The intention prediction of student participation in learning behavior is different from the natural language processing tasks targeted by traditional multi-head self-attention. In the intention prediction scenario of our students participating in learning behavior, the behaviors between students and different learning resources and different interactive objects are one-way, that's, these behaviors are only affected by historical behaviors. In order to solve this problem, on the basis of the multi-head self-attention mechanism, this article adds a directional mask matrix for preserving the temporal unidirectional information of the student behavior sequence, and constructs a multi-intent self-attention module. The directional mask matrix *N* satisfies:

$$N_{ij} = \begin{cases} 0, i < j \\ -\infty, otherwise \end{cases} \tag{2}$$

It's assumed that the hidden output from a time-aware *LSTM* is represented by $A = [f_1, \ldots, f_m]$, the query, key and value vectors are represented by W_i, L_i and $U_i \in R^{m\times c}$ respectively. A single head attention is represented by $head_i \in R^{m\times cl}$, the weight matrix of the output linear transformation is represented by $Q^t \in R^{fcl\times c}$, the number of heads in the multi-head mechanism is represented by *f*, and $c_l = f/c$. The following formula gives the calculation formula of the multi-intent self-attention module:

$$\begin{gathered}
W_i = Q_i^W A; L_i = Q_i^L A; U_i = Q_i^U A\\
head_i = soft\max\left(\frac{W_i L_i^T}{\sqrt{c_l}} + N\right)U; C = multihead(A) = Q^o concat(head_i, \ldots, head_f)
\end{gathered} \tag{3}$$

The final output of this module is $C \in R^{m \times c}$, which captures the intention information of each student participating in the learning behavior.

Although different students have similar histories of interactive behaviors, they may have very different intentions to participate in learning behaviors because of their differences in personal preferences. To this end, this article constructs an attention network capable of simulating personalized, adaptive behavioral intent representations based on a multi-intent self-attention module. The network details are represented by:

$$\beta_l = \frac{\exp(p_v C^T)}{\sum_{l=1}^{o} \exp(p_v C^T)}, s^u = \sum_{k=1}^{t} \alpha_k Z \tag{4}$$

Assuming that the student embedding including the student's age, gender, grade, major and other information is represented by p_v, the short-term behavior representation of student v during the participation in the learning process can be represented by the final output r^v of the personalized attention network. By weighting and combining the output of the multi-intent self-attention module, the model fully considers the characteristics of students' learning preferences, and finally achieves the goal of personalization.

After the processing of the above modules, the students' participation in learning behavior intention can be predicted from the sequence of students' participation in learning behavior. In order to effectively capture the long-term global dependencies across the entire student history, the representations of different participating learning behaviors are taken as input, processed through a traditional multi-head self-attention mechanism, and the output is put into the prediction layer of the next layer. Assuming that the final output of the students' L learning behaviors is represented by $R = [r_1^v, \ldots, r_m^v]$ and the output of the attention mechanism between student learning behaviors is represented by $T = [t_1^v, \ldots, t_L^v]$, the specific formula is represented by the following formula:

$$\begin{gathered} W_i = Q_i^W R; L_i = Q_i^L R; U_i = Q_i^U R \\ head_i = soft\max\left(\frac{W_i L_i^T}{\sqrt{c_l}}\right) U; C = multihead(R) = Q^o concat(head_i, \ldots, head_f) \end{gathered} \tag{5}$$

Finally, the final output C of the module is put into the multi-layer perceptron to obtain the final result vector of the intention prediction of students' participation in learning behaviors. Figure 4 shows the model calculation process.

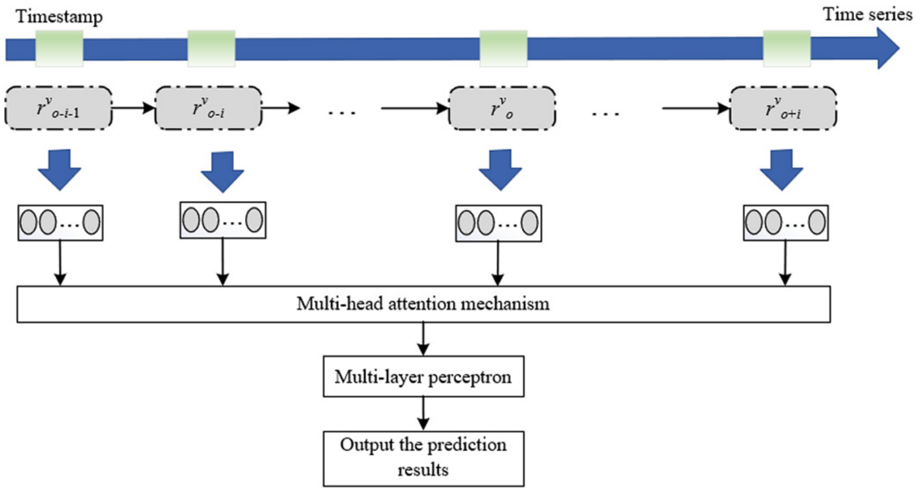

Fig. 4. Model calculation process

3 Evaluation of students' learning autonomy

There is a close relationship between student learning autonomy and student learning enthusiasm. Learning initiative refers to the ability and willingness of students to actively seek knowledge, solve problems and participate in activities during the learning process. Learning enthusiasm refers to the degree of enthusiasm, interest and engagement that students show in the learning process. The two influence each other and work together to drive students to achieve better learning outcomes. This article judges students' learning enthusiasm through the evaluation results of students' learning autonomy. Evaluation indicators include whether to set reasonable learning goals, to formulate feasible learning plans, to use rich learning strategies, and to implement self-monitoring.

The evaluation of students' learning autonomy based on machine learning algorithms can reduce the influence of human factors on the evaluation results and provide more objective and fair evaluation results. At the same time, compared with traditional teacher evaluation methods, machine learning can analyze a large amount of data in a short period of time and improve evaluation efficiency. This article constructs a network model for the evaluation of students' learning autonomy. The network model consists of a spatial self-attention module and a polarity detection branch. It uses the learning autonomy category label to guide the learning of evaluation tasks, and finally outputs the rating results of student learning autonomy.

It's assumed that $\{A,B,C\} = \{(a_i,b_i,c_i)\}_{i=1}^{N}$ is a training set containing M evaluation index samples, where students are represented by $x_i a_i$ and the fine-grained learning autonomy category label of a_i is represented by $b_i \in \{0, \ldots, D-1\}$, that's, the learning autonomy category label, the number of learning autonomy categories is represented by D, and the coarse-grained learning autonomy category label of a_i is represented by

c_i {0,1}, that's, the polarity learning autonomy category label. In this article, a multi-task loss function is designed to assist the parameters of the constructed model in sample learning. It's assumed that the loss item that constrains the final classification result is represented by L_d, the loss item that constrains coarse-grained learning autonomy classification is represented by L_t, the loss item that constrains fine-grained learning autonomy category is represented by L_t, and the weighting coefficient of loss item L_t is represented by μ, then there is a definition formula:

$$L = L_d + L_t + L_q \tag{6}$$

In order to realize the final learning autonomy classification learning of the model and ensure that the spatial self-attention module learns the correlation between evaluation indicators more accurately, this article constructs a loss function L_d to carry out related constraints. Assuming that the prediction value of the fine-grained learning autonomy category of sample a_i is represented by $u_i \in R^D$, then:

$$L_d = -\frac{1}{M}\sum_{i=1}^{M}\sum_{j=1}^{D} b_i^j \log(u_i^j) \tag{7}$$

In order to implement the model for coarse-grained learning autonomy classification learning and ensure that the polarity detection branch can more accurately predict the coarse-grained learning autonomous category, this article constructs a loss function L_t for related constraints. Assuming that the prediction value of the coarse-grained learning autonomy category of sample a_i is represented by $v_i \in R^2$, then:

$$L_t = -\frac{1}{M}\sum_{i=1}^{M}\sum_{j=1}^{D} c_i^j \log(v_i^j) \tag{8}$$

In order to realize the network's learning of the correlation between coarse-grained and fine-grained learning autonomy, L_q is designed to carry out relevant constraints. Assuming that the classification result of the coarse-grained learning autonomy predicted by the polarity detection branch is represented by v_i, and the summed fine-grained learning autonomy category result is represented by u_i', then:

$$L_q = -\frac{1}{M}\sum_{i=1}^{M}\sum_{j=1}^{2} u_i^j \log(u_i'^j) \tag{9}$$

The calculation formula of u_i' is:

$$u_i' = Sum_v(u_i) \tag{10}$$

4 Combined model principle based on inverted error method

Based on the obtained intention prediction of student participation in learning behaviors and the evaluation results of students' learning autonomy, this article uses the inverted error method to weight and establish a combined model to predict the regression of students' learning enthusiasm. That is to use the corrected prediction error to carry out the error reciprocal method weighting, and build a combined prediction model based on the intention prediction of students' participation in learning behaviors and the evaluation results of students' learning autonomy to predict students' learning enthusiasm. Firstly, the inverted error method is used to weight the intention prediction of students' participation in learning behaviors and the evaluation results of students' learning autonomy. It's assumed that the prediction error of the *i*-th model is represented by γ_i, and the number of prediction models is represented by *m*, which is 2 herein. The weight of the *i*-th model in the prediction model is represented by θ_i, then:

$$\theta_t = -\frac{\gamma_i^{-1}}{\sum_{i=1}^{m} \gamma_i^{-1}} \tag{11}$$

Based on the corrected prediction error, the prediction and evaluation results are weighted by the inverted error method. It's assumed that *g*1 *is* the predicted intention value of students' participation in learning behaviors, *g*2 is the evaluation value of students' learning autonomy, and *g* is the predicted value of the combined model. Based on the above formula, there are following formulas:

$$\theta_1 = -\frac{\gamma_2}{\gamma_1 + \gamma_2} \tag{12}$$

$$\theta_2 = -\frac{\gamma_1}{\gamma_1 + \gamma_2} \tag{13}$$

$$g = \theta_1 g_1 + \theta_2 g_2 \tag{14}$$

From the above three formulas, the above method can reduce the prediction error of the combined model on students' learning enthusiasm by assigning a smaller weight to the prediction model with a larger error and assigning a larger weight to the prediction model with a smaller error, and improve the overall prediction accuracy of the model.

5 Experimental results and analysis

First of all, this article conducts a descriptive analysis of the change of college students' learning enthusiasm in the behavioral dimension. The results of the analysis are shown in Table 1. Here, the behaviors of college students' learning enthusiasm are divided into five categories: "Completely incompatible", "Incompatible", "Compatible", "More compatible", and "Completely compatible". It can be seen from the table that in the dimension of learning behavior change, 35.6% of the students expressed that they are willing to actively participate in classroom discussions, and are willing to answer or ask questions from teachers; 31.6% of the students are willing to actively read English books, articles, magazines, etc. after class in order to broaden their vocabulary and improve their reading comprehension; 33.6% of the students are willing to spend time memorizing words, doing exercises, practicing oral English, etc. after class; 29.5% of students will actively search for learning resources in the learning process to realize their own learning plans; 25.4% of the students are more willing to participate in English activities such as English corners, speech contests, and English drama performances; 20.8% of students make friends with international students and participate in language exchange activities to improve oral skills and cultural understanding; 34.2% of the students try to write diaries, stories or poems in English in order to improve their writing and expression skills; 46.6% of the students express their strong interest in English learning; 40.1% of the students indicate that they would pass an English test or reach a specific language level, and make plans to achieve these goals; 39.2% of the students say that they would not give up even if they encountered difficulties and setbacks in the process of English learning.

Table 1. Descriptive analysis of the change of college students' learning enthusiasm in the behavioral dimension

Behavior	Completely Incompatible	Incompatible	Compatible	More Compatible	Completely Compatible	Chi-Square	P Value
1	72 (3.6%)	113 (5.6%)	432 (21.4%)	676 (33.5%)	727 (35.9%)	922.154^2	.000
2	82 (4%)	311 (15.4%)	529 (26.2%)	583 (28.9%)	511 (25.5%)	436.581^2	.000
3	98 (4.8%)	365 (17.8%)	596 (29.1%)	573 (28%)	413 (20.3%)	388.856^2	.000
4	81 (4%)	269 (13.5%)	621 (31.1%)	548 (33.5%)	481 (26.2%)	496.256^2	.000
5	81 (3.5%)	114 (5.2%)	447 (21.5%)	663 (31.8%)	705 (32.6%)	836.164^2	.000
6	86 (4.4%)	335 (17.1%)	524 (25.7%)	563 (21.8%)	518 (25.6%)	409.261^2	.000
7	92 (4.9%)	355 (16.2%)	575 (26.8%)	566 (27.4%)	426 (20.3%)	345.856^2	.000
8	85 (4.4%)	272 (12.6%)	606 (39.1%)	551 (27.3%)	426 (26.2%)	497.156^2	.000
9	83 (4.1%)	307 (15.3%)	512 (25.2%)	591 (29.7%)	547 (26.2%)	435.981^2	.000

Theoretically, the probability of selecting five categories should be equal to one-fifth, but from the P values of each category in the table, we can see that the frequency distribution of the number of students in the five categories is obviously different from the expected one-fifth.

This article verifies the validity of the intention prediction model of students' participation in learning behaviors, and the selected model evaluation indicators include *Recall@*10 and *MRR* indicators. In the experiment, the two parameters of the hidden layer dimension of *the LSTM* network and the number of multi-heads of the self-attention module are changed from 2, 4, 8 and 16 and 16, 32, 64 and 128 respectively, and the value evolution of the two model evaluation indicators is observed. The experimental results are given in Figures 5 and 6.

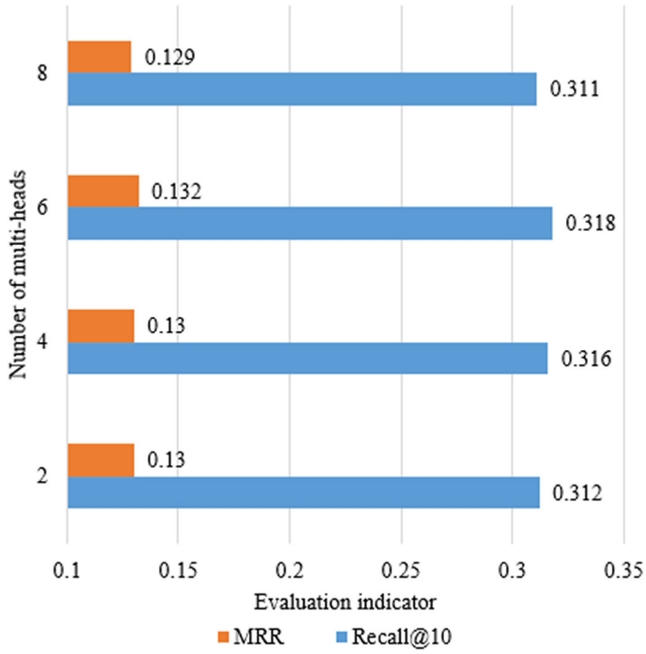

Fig. 5. Model performance under different hidden layer dimensions

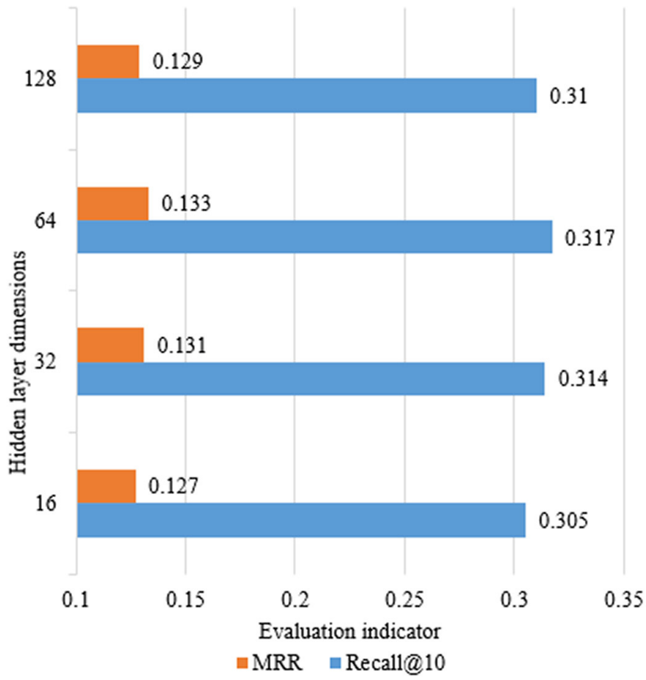

Fig. 6. Model performance under different number of multi-heads

It can be seen from the figure that when the hidden layer dimension of *the LSTM* network is set to 64 and the number of multi-heads is set to 8, the two model evaluation indicators show that the model performance at this time is the best, and the prediction effect is the best. The main reason is that more embedding dimensions can increase the performance of the model to a certain extent, but too high embedding dimensions will generate more noise and lead to a decrease in model performance. This is because students' intention in learning behaviors is often complex, it the number of multi-heads is too fewer to extract such information, and too many to make it difficult to learn the model, so it is both not feasible to setting too many or too less multi-heads.

Normal distribution analysis is the basis for studying the correlation of sample variables of students' online learning autonomy evaluation indicators. Therefore, this article uses SPSS19.0 to determine whether students can set reasonable learning goals, make feasible learning plans, and use rich learning strategies and implementing self-monitoring with the PP diagram, which is helpful for the next step of correlation analysis. Figure 7 of observation and analysis shows that the four categories and students' online learning autonomy are normally distributed, and model prediction performance comparison and analysis can be performed in the next step.

This article compares and analyzes the prediction results of the intention prediction model on student participation in learning behaviors and the student learning autonomy evaluation model before and after improvement. The comparison results are given in Table 2.

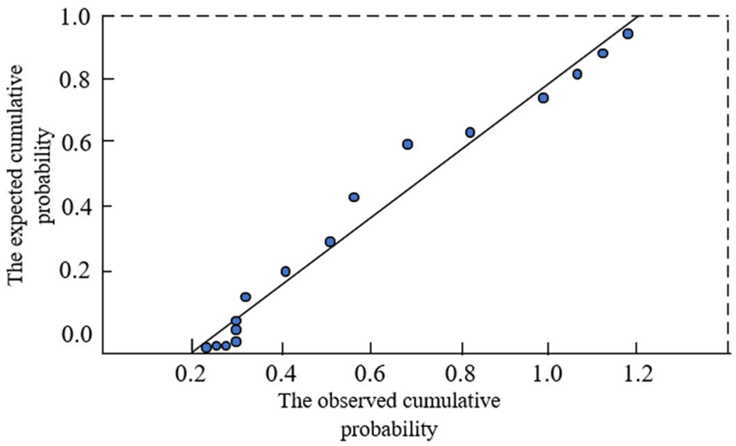

Fig. 7. Normal distribution PP diagram of students' online learning autonomy

Table 2. Comparison of prediction performance before and after model improvement

Prediction Models		Evaluation Indicators		
		R^2	*MAE*	*RMSE*
Original model	*LSTM* module before improvement	0.987251	0.003658	0.004196
	Traditional BP neural network	0.285412	0.236472	0.000684
Optimized model	Before introducing the personalized attention network	0.985234	0.003102	0.003869
	Before correlation study	0.856135	0.008164	0.000156
Final model	Prediction model	0.965451	0.002158	2.356843e-06
	Evaluation model	0.863465	0.002548	0.000268

It can be seen from the table that the performance of the improved intention prediction model of students' participation in learning behaviors and the evaluation model of students' learning autonomy is better. Further, this article compares and analyzes the combined prediction results of the original model based on the modified *MAE* and *RMSE* weighting, the optimized model and the final model. The comparison results are given in Table 3.

In the process of weight setting, it is found that the combined model based on the modified *MAE* weighting has serious bias in weight distribution, which makes the learning degree of the prediction model of students' participation in learning behavior far greater than the learning degree of the evaluation model of students' learning autonomy. Through comparison, it is found that the combined model based on the modified *RMSE* weighting is better than the combined model based on the modified *MAE* weighting in predicting students' learning enthusiasm, and the *RMSE* has dropped by nearly one-third.

Table 3. Comparison of prediction performance of combined models

Combined Models		Model Prediction Evaluation Indicators		
		R^2	*MAE*	*RMSE*
Weighting based on modified *MAE*	Combining the original model	0.865161	0.012165	0.000196
	Combining optimized model	0.906541	0.008561	0.000126
	Combining the final model	0.986217	0.003647	2.521642 e-05
Weighting based on modified *RMSE*	Combining the original model	0.984641	0.002498	0.003687
	Combining optimized model	0.963543	0.002154	0.000354
	Combining the final model	0.956324	0.002315	1.834546 e-05

6 Conclusions

Taking English learning as an example, this article studies the prediction model of students' learning enthusiasm based on combinatorial optimization algorithm, expounds in detail the main manifestations of students' learning enthusiasm, predicts the intention of students to participate in learning behaviors based on the enumerated behaviors, so as to judge students' learning enthusiasm, and gives the construction method of the prediction model. This article constructs a network model for the evaluation of students' learning autonomy, and finally outputs the grade results of students' learning autonomy evaluation. Based on the obtained intention predictions of students' participation in learning behaviors and the evaluation results of students' learning autonomy, a combined model is established through the weighting of the inverted error method to predict the regression of students' learning enthusiasm.

Combined with the experiment, it makes the descriptive analysis of the change of college students' learning enthusiasm in the behavior dimension, and gives the corresponding analysis results. It verifies the validity of the prediction model of students' participation in learning behaviors. By adjusting the two parameters of the hidden layer dimension of the *LSTM* network and the number of multi-heads of the self-attention module, the evolution of two model evaluation indicators of *Recall* @10 and *MRR* is observed, and finally a reasonable parameter setting value is given. It draws the normal distribution *PP* diagram of students' online learning autonomy, verifies that the four dimensions and students' online learning autonomy are in a normal distribution, and carries out the model prediction performance comparison analysis in the next step. The comparison and analysis of the prediction results of intention prediction model of the students' participation in learning behaviors and the student learning autonomy evaluation model before and after improvement verifies the effectiveness of the single models and combined models constructed in this article.

7 References

[1] Roumba, E., Nicolaidou, I. (2022). Augmented reality books: Motivation, attitudes, and behaviors of young readers. International Journal of Interactive Mobile Technologies, 16(16): 59–73. https://doi.org/10.3991/ijim.v16i16.31741

[2] Liu, W., Bi, S. (2023). Influence mechanism of students' learning enthusiasm based on educational big data. International Journal of Emerging Technologies in Learning, 18(6): 96–109. https://doi.org/10.3991/ijet.v18i06.38717

[3] Li, J., Ke, X. (2018). Study on the opportunities and realization route of college students' ideological and political education against the backdrop of the "Belt and road" initiative. In Proceedings of the 2018 1st International Conference on Internet and e-Business, pp. 359–363. https://doi.org/10.1145/3230348.3230454

[4] Roumba, E., Nicolaidou, I. (2022). Augmented reality books: Motivation, attitudes, and behaviors of young readers. International Journal of Interactive Mobile Technologies, 16(16): 59–73. https://doi.org/10.3991/ijim.v16i16.31741

[5] Khalilov, T. (2022). Formation and development of education in Nakhchivan (End of the XIX Century Before the Early XX Century). Journal of Corporate Governance, Insurance, and Risk Management, 9(2): 365–373. https://doi.org/10.56578/jcgirm090207

[6] Darbali-Zamora, R., Cobo-Yepes, N., Ortiz-Rivera, E.I., Aponte-Bezares, E.E., Rincón-Charris, A.A. (2018). Applying HOL/PBL to prepare undergraduate students into graduate level studies in the field of aerospace engineering using the Puerto Rico Cubesat project initiative. In 2018 IEEE Frontiers in Education Conference (FIE), pp. 1–8. https://doi.org/10.1109/FIE.2018.8659049

[7] Baturina, L. Simakov, A. (2023). Students' attitude towards E-learning in Russia after pandemic. Education Science and Management, 1(1): 1–6. https://doi.org/10.56578/esm010101
[8] Lei, C.U., Wei, H.Q. (2022). Developing student's global competencies at scale in an affordable MOOC K12 outreach initiative. In Proceedings of the Ninth ACM Conference on Learning Scale, pp. 321–324. https://doi.org/10.1145/3491140.3528307
[9] Sergeyev, A., Alaraje, N., Kuhl, S.A., Li, B. (2016). Culminating phase of open source programmable logic controller software development initiative for high school students, two-and four-year colleges, and displaced workers. In 2016 ASEE Annual Conference & Exposition. https://doi.org/10.18260/p.26617
[10] Buffum, P.S., Frankosky, M.H., Boyer, K.E., Wiebe, E.N., Mott, B.W., Lester, J.C. (2016). Empowering all students: Closing the CS confidence gap with an in-school initiative for middle school students. In Proceedings of the 47th ACM technical symposium on computing science education, pp. 382–387. https://doi.org/10.1145/2839509.2844595
[11] Inoa, R., Sullivan, K., Giordano, K., Wynarczuk, K. (2022). The process of developing a hybrid interprofessional education initiative for graduate students. Higher Education Pedagogies, 7(1): 179–200. https://doi.org/10.1080/23752696.2022.2137055
[12] Huvard, H., Bayat, H., Way, S., Brewer, C., Miller, A., Garcia, A. (2022). Engineering education enrichment (e3) initiative: A co-curricular program intended to improve persistence and career success for low-income and first-generation engineering students. In 2022 ASEE Annual Conference & Exposition, pp. 1–12.
[13] Shi, C. (2022). College students' behavior initiative, psychological availability, and innovation and entrepreneurship: The mediating effect of interest orientation. International Journal of Emerging Technologies in Learning, 17(17): 192–206. https://doi.org/10.3991/ijet.v17i17.34175
[14] Xi, L., Wen, B., Zhao, H. (2022). Analysis of the correlation between the mental stress of college students and their learning initiative during the outbreak of COVID-19. International Journal of Emerging Technologies in Learning, 17(23): 145–159. https://doi.org/10.3991/ijet.v17i23.35933
[15] Mittal, P. (2021). THINK lab: An initiative to foster creative and critical thinking amongst first year design students. In Design for Tomorrow-Volume 2: Proceedings of ICoRD 2021, pp. 305–319. https://doi.org/10.1007/978-981-16-0119-4_25
[16] Ranjan, R., Lekan, K., Bhaip, V. (2021). Designing the UVA open data initiative: Increasing engagement for students, faculty, staff members, and other stakeholders. In 2021 Systems and Information Engineering Design Symposium (SIEDS), pp. 1–6. https://doi.org/10.1109/SIEDS52267.2021.9483750
[17] Zhao, S., Song, J. (2020). Students' perceptions of a learning support initiative for b-MOOCs. International Journal of Emerging Technologies in Learning (iJET), 15(21): 179–194. https://www.learntechlib.org/p/218366/; https://doi.org/10.3991/ijet.v15i21.17153
[18] Galishnikova, E., Khusainova, A., Kudryavtseva, M., Mardanshina, R. (2020). University students' cognitive initiative in the process of foreign language learning. International Multidisciplinary Scientific GeoConference: SGEM, 20(5.2): 895–902. https://doi.org/10.5593/sgem2020/5.2/s22.111
[19] Farooq, A., Hakkala, A., Virtanen, S., Isoaho, J. (2020). Cybersecurity education and skills: Exploring students' perceptions, preferences and performance in a blended learning initiative. In 2020 IEEE Global Engineering Education Conference (EDUCON), pp. 1361–1369. https://doi.org/10.1109/EDUCON45650.2020.9125213
[20] Gunasagaran, S., Mari, M.T., Srirangam, S., Kuppusamy, S. (2019). Adoption of social media by architecture students in fostering community SERVICE initiative using technology acceptance model. In IOP Conference Series: Materials Science and Engineering, 636(1): 012015. https://doi.org/10.1088/1757-899X/636/1/012015

[21] Wright, K. (2019). Freshman-year initiative for a cohort of largely engineering minority students. In 2019 ASEE Annual Conference & Exposition. https://doi.org/10.18260/1-2--32860
[22] Brozina, C., Johri, A., Naderi, N. (2019). Engineering time: Learning analytics initiative to understand how first-year engineering students spend their time. In 2019 ASEE Annual Conference & Exposition. https://doi.org/10.18260/1-2--32742
[23] Wang, X.L. (2021). Research on the motivation and improvement countermeasures of students' learning initiative based on factor analysis. ACM International Conference Proceeding Series, pp. 247–253. https://doi.org/10.1145/3511716.3511755

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