Prediction of College Students' Classroom Learning Effect Considering Positive Learning Emotion

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Abstract—Exploring the influence of positive learning emotion on college students' classroom learning effect facilitates fully understanding college students' online learning effect and emotional state, and is beneficial to improving students' learning quality and teachers' teaching quality. At present, few scholars have summative evaluation of students' classroom learning effect from the perspective of students' learning emotions and prove from the perspective of theory and practice that good emotional state is an important influencing factor to improve college students' classroom learning effect. Therefore, this article fully considers the positive learning emotion, and makes a research on the prediction of college students' classroom learning effect. Firstly, this article defines the behavior data of students in the online learning process based on learning emotions, and studies the correlation between college students' classroom learning behaviors based on Hawkes process. Then, based on the learning participation under the influence of different learning emotions, the online learning effect of students is quantified, and the prediction model of students' classroom learning is constructed by combining the learning behavior sequence analysis results represented by Hawkes process and the characteristic information of students themselves and courses. The experimental results verify the effectiveness of the model, and the significance test results confirm the positive effect of positive emotion on learning effect.

Keywords—Positive learning emotion, online learning for college students, prediction of learning effect

1 Introduction

In recent years, with the rapid development of online tutoring platform, more and more college students have obtained freer online learning opportunities than traditional learning methods [1–5], but at the same time, college students have exposed problems such as lack of learning enthusiasm, insufficient learning continuity or learning confusion and increased psychological burden under the influence of negative emotion [6–10]. In order to avoid the above problems, whether from the perspective of learning or emotions, it is necessary to explore the influence of positive learning emotion on college students' classroom learning effect [11–19], so as to fully understand college students' online learning effect and emotional state, improve students' learning quality, and provide theoretical basis and ideas for improving teachers' teaching quality and making reasonable teaching decisions [20–24].

Nho et al. [25] puts forward a model to predict learning results and recommends courses for undergraduates and proposes a method based on machine learning technology and recommendation system. With the participation of 580 students, the model is tested with the grade data of 22 courses. The results show that 68.2% of the students think the system is useful to them. Le et al. [26] summarizes the research results of identifying influencing factors in the online learning stage of blended learning courses. According to these factors, a model for predicting students' grades is proposed. With a course of 231 participants, several models are developed to predict students' learning results. Learning analysis and machine learning techniques are used to analyze the data obtained from LMS system log files, and the results show that four factors, namely, the number of browsing, the number of posts, the number of forum browsing and the number of homework submitted on time, have an impact on students' learning results. One of the difficulties faced by online learners is the lack of regular supervision and the need to provide guidance to support the learning process more effectively. The analysis of learning data in online courses not only becomes more and more important in predicting learning results, but also provides effective teaching strategies for learners to help them get the best results. Nguyen et al. [27] proposes a model for predicting learning results based on the interaction between learners and online learning systems, which monitors and defines online learners by providing learning analysis dashboards for learners and teachers. This method is mainly based on some machine learning and data mining technologies. The results show that 75% of the students' results are close to the predicted results, and the accuracy rate exceeds 50%. Livieris et al. [28] proposes an integrated semi-supervised algorithm for predicting students' performance in the final exam at the end of the year. Experimental results show that compared with some classical classification algorithms, the proposed algorithm has efficiency and robustness in accuracy.

At present, scholars at home and abroad have carried out research on positive learning emotion and classroom learning effect of college students, and achieved some research results. With the help of students' attendance, classroom performance, answering questions and homework completion, relevant scholars use percentile scores to assess college students' classroom learning effect. Some scholars believe that a good emotional state can promote the learning enthusiasm of college students and make them have more self-confidence to complete the academic tasks assigned by teachers. There is a close relationship between positive emotion and students' learning engagement. However, few scholars have summative evaluation of students' classroom learning effect from the perspective of students' learning emotions and prove from the perspective of theory and practice that good emotional state is an important influencing factor to improve college students' classroom learning effect. Therefore, this article fully considers the positive learning emotion, and makes a research on the prediction of college students' classroom learning effect. Firstly, the second chapter of the article defines the behavior data of students in the online learning process based on learning emotions, and studies the correlation between college students' classroom learning behaviors based on Hawkes process, giving an optimized Hawkes process framework. Then, based on the learning participation under the influence of different learning emotions, the third chapter of the article quantifies the online learning effect of students, and constructs the prediction model of students' classroom learning by combining the learning behavior sequence analysis results represented by Hawkes process and the characteristic information of students themselves and courses. The experimental results verify the effectiveness of the model, and the significance test results confirm the positive effect of positive emotion on learning effect.

2 Learning behavior sequence under the influence of different learning emotions

Different from the traditional face-to-face teaching situation, teachers who implement online teaching cannot judge students' learning status by their facial expressions, eyes and movements. In order to form an effective monitoring mechanism of learning state in online teaching environment, this article defines the behavior data of students in online learning process based on learning emotions, that's, general learning behavior, negative learning behavior and positive learning behavior. Because the above three types of behaviors occur alternately in the learning process, it is difficult to characterize them in the traditional tabular form. Therefore, this article defines the learning behavior sequence under the influence of different learning emotions, and forms an orderly data structure to represent the learning behaviors under the influence of different online learning emotions. This sequence reflects the mixed learning behavior data flow in the online learning process of college students. Specifically, the learning behavior under the influence of different learning emotions is defined as four tuples (student ID, teaching activity ID, timestamp and behavior type). The *k*-th learning behavior of a student at the timestamp o_k is represented by p_k, and $p_k \in$ {represents general learning behavior, negative learning behavior, positive learning behavior}. The total number of learning behaviors is expressed by M_p, and the following formula gives the expression of learning behavior sequence under the influence of different learning emotions:

$$R^{Mp} = \{(p_k, o_k)\}_{k=1}^{M_p} \tag{1}$$

The expression form of learning behavior sequence data has a great influence on predicting the success of college students' classroom learning effect. In order to extract more effective information, this article simplifies the complex learning behavior sequence data, that's, the learning behavior sequence is mapped in real dimension vector space. It is assumed that the vector space is represented by $|\Phi|\times m$, the number of learning behaviors under the influence of different learning emotions in the vector space is represented by $|\Phi|$, the vector dimension of learning behaviors under the influence of different learning emotions is represented by m, the learning behavior sequence under the influence of different learning emotions is represented by R, the *i*-th behavior in R is represented by p_i, and the number of behaviors in the sequence of behaviors is represented by n. R can be expressed by:

$$R = ((p_1, o_1)(p_2, o_2), \ldots, (p_i, o_i), \ldots, (p_n, o_n)) \tag{2}$$

The input of the mapping function g: $R \rightarrow U$ is R, and the output is the relationship vector used to quantify the dynamic pattern of students' learning behavior under the influence of different learning emotions:

$$U = [u_i]_{i=1}^{M_p} \tag{3}$$

The vector is a time-varying vector that changes with time.

All learning behaviors of students in the process of online learning are interrelated, so the correlation between learning behaviors is very important to predict college students' classroom learning effect. After completing the generation of online learning behavior sequence of students on each timestamp, this article studies the correlation between college students' classroom learning behaviors based on *Hawkes* process, so as to achieve a more accurate representation of online learning behavior.

Based on the classical *Hawkes* process, it can be assumed that a certain type of learning behavior in the past online learning process can improve the probability of this type of learning behavior in the future, and the incentive of past learning behavior is positive and its influence on the current learning behavior of the same type is exponentially attenuated with time. Assuming that the occurrence probability of a certain type of learning behavior l is expressed by $\mu_l^*(o)$, the basic strength of this process is expressed by $\lambda_l \geq 0$, the incentive degree of the same type of learning behavior i to the past learning behavior l is expressed by $\beta_{il} \geq 0$, the time when the current learning behavior occurs is expressed by o, the time when the past learning behavior i occurs is expressed by o_i, the time attenuation coefficient is expressed by ξ, and the attenuation degree of the influence of the past learning behavior with time is expressed by $p^{-\xi(o-oi)}$, then:

$$\mu_l^*(o) = \lambda_l + \sum_{i:o_i<o} \beta_{il} p^{-\xi(o-o_i)} \tag{4}$$

Hawkes process has a positive effect constraint on representing learning behavior under the influence of different learning emotions, which limits the expressiveness of learning behavior under the influence of different learning emotions, resulting in the following two problems: 1) Because β_{il} is always positive, it is impossible to analyze the inhibitory effect between different types of learning behaviors in students' online learning process; 2) Because λ_l can't be less than 0, it is impossible to analyze the negative effects of students' learning behaviors in the process of online learning. To solve the above problems, this article extends the expressiveness of Hawkes process. Firstly, the value range of β_{il} and λ_l of less than 0 is redefined, and a nonlinear function g_l is set to ensure that the strength function is always greater than 0:

$$\mu_l(o) = g_l(\mu_l^*(o)) \tag{5}$$

$\mu_l(o)$ will increase or decrease with the change of o, and represents the incentive and inhibitory effects between students' learning behaviors under the influence of different learning emotions. The influence of a certain type of past learning behavior decreased from ξ to 0, and its intensity approaches $g(\lambda_l + 0)$. In order to ensure that the intensity value is always positive when a certain type of learning behavior may occur, and considering the sensitivity of Hawkes process to time units, this article sets g_l as follows:

$$g(a) = r\log(k + \exp(a / r)) \tag{6}$$

In the above formula, r is the proportional coefficient controlling the curvature of $g(a)$, satisfying $r > 0$. Assuming that the scale factor of learning behavior l is represented by r_l, the following formula gives the instantiation expression of formula 4:

$$\mu_l(o) = r_l \log(1 + \exp(\mu_l(o) / r_l)) \tag{7}$$

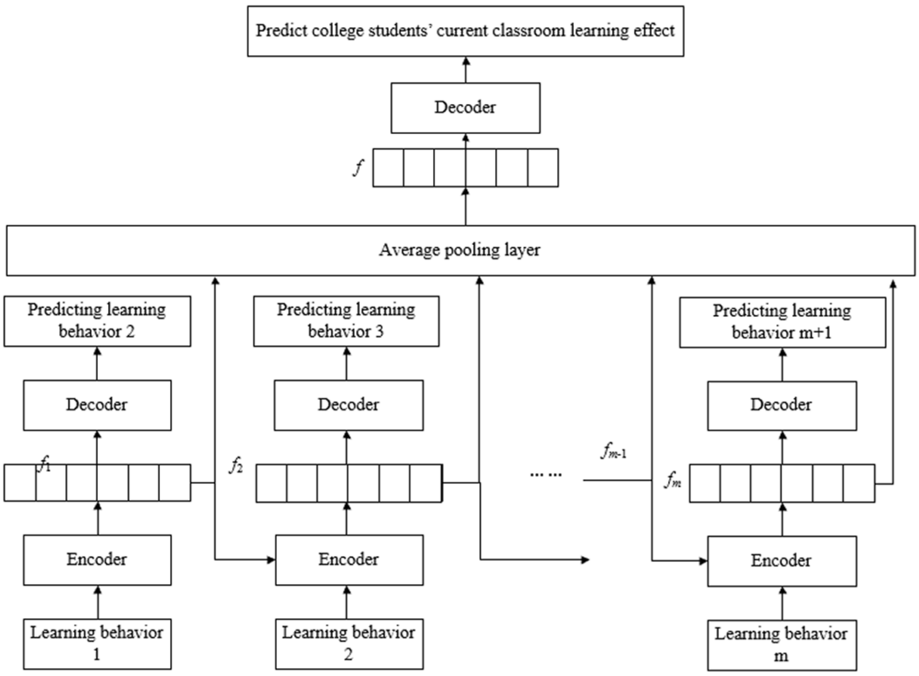

Fig. 1. Schematic diagram of optimized Hawkes process framework

Figure 1 shows the schematic diagram of the optimized *Hawkes* process framework. The prediction of $\mu_l(o)$ by *Hawkes* process is only completed by summation operation, but the use of learning behavior sequence under the influence of different learning emotions can solve the problem that past learning behaviors have independent and additive effects on $\mu_l(o)$. In order to fully understand the learning behavior sequence data, this article introduces the State unit of cyclic neural network, which makes the current input and past input of the model corresponding to each position on the learning behavior sequence establish a certain correlation. $\mu_l(o)$ gradually approaches λ_l with the occurrence of different types of learning behaviors. In this process, the hidden state $f(o)$ determines the size of $\mu_l(o)$, that's:

$$\mu_l(o) = g_l(Q_l f(o)) \tag{8}$$

However, in actual experiments, it is found that the gradient instability is easy to occur in the training process of cyclic neural network. In order to solve this problem, LSTM network model is introduced in this article. In this model, $f(o)$ is determined by the cell state $XB(o)$, that's:

$$f(o) = t_i \oplus (2\chi(2XB(o)) - 1) \tag{9}$$

The $XB(o)$ expression determined by the past behavior sequence is as follows:

$$d(o) \overset{def}{=} \bar{d}_{i+1} + (d_{i+1} - \bar{d}_{i+1})\exp(-\xi_{i+1}(o - o_i)) \tag{10}$$

It can be seen from the above formula that the probability of learning behavior at any time is certain. The randomness of this process depends on the next learning behavior and its occurrence time. No matter which type of learning behavior occurs first, it will be fed back to the prediction model. If the intensity of a certain type of learning behavior is too low, the next type of learning behavior may appear for a long time.

3 Construction of learning effect prediction model

Figure 2 shows the learning emotion theory in the process of online learning. It can be seen from the figure that students' choice, organization and integration of knowledge are not only influenced by emotions, but also by their own cognitive state, previous knowledge experience, curriculum knowledge system and so on. Accurately describing students' learning presentation through the interaction process between students and course content has become a key problem in the prediction process of prediction model. However, traditional prediction methods tend to ignore the influence of other feature information on students' learning behavior in the actual scenario of predicting learning effect, which further leads to the lack of interpretability of prediction results. Therefore, this article firstly quantifies the students' online learning effect based on the learning participation under the influence of different learning emotions, and combines the analysis results of the learning behavior sequence represented by *Hawkes* process, taking full account of the influence of students themselves and the course they have learned on the learning effect prediction results, so as to obtain ideal prediction results. In this article, learning participation is determined as the ratio of the duration of active learning behavior to the total learning duration, and students' online learning effect can be quantified by the following formula:

$$TRW = O_{ST} / O_{TO} \tag{11}$$

In the actual experiment, it can be found that there may be great differences in learning effect among students with similar learning behavior sequences, mainly because different students have different cognitive levels. Therefore, when the model predicts learning effect, it can't only refer to the data of students' learning behavior.

In order to improve the interpretability of the prediction results, this article incorporates the characteristic information of students themselves and the courses they have learned into the model. Assuming that the number of students is represented by *n* and the dimension of student vector is represented by *m*, the following formula gives the expression of student feature matrix:

$$S=\begin{bmatrix} s_{11} & s_{12} & \dots & s_{1m} \\ s_{21} & s_{22} & \dots & s_{2m} \\ \dots & \dots & \dots & \dots \\ s_{n1} & s_{n2} & \dots & s_{nm} \end{bmatrix} \tag{12}$$

The feature vector of each student can be expressed by the following formula:

$$s=[s_{n1},s_{n2},\dots,s_{nm}] \tag{13}$$

Similarly, the following formula gives the expression of curriculum feature matrix:

$$D=\begin{bmatrix} d_{11} & d_{12} & \dots & d_{1m} \\ d_{21} & d_{22} & \dots & d_{2m} \\ \dots & \dots & \dots & \dots \\ d_{n1} & d_{n2} & \dots & d_{nm} \end{bmatrix} \tag{14}$$

The feature vector of each course can be expressed by the following formula:

$$d=[d_{n1},d_{n2},\dots,d_{nm}] \tag{15}$$

According to the current learning behavior sequence, the fusion feature vector shown in the following formula can be obtained by multiplying *s* and *d*:

$$p_r = s \oplus d \tag{16}$$

Figure 3 shows the fusion feature vector generation process. Because the prediction results of students' online learning effect depend on the learning behavior patterns under the influence of different learning emotions, and the characteristic information of students themselves and the courses they have learned. Based on the above considerations, the characterization vectors of learning behavior sequence obtained by Hawkes process and the fusion feature vectors of the above formula are added to each other, and the operation results will be used as model input to classify and predict learning effect.

The prediction results need to be processed by the fully connected layer before being output. Assuming $Q \in R^{n\times m}$, *n* is equal to the dimension of the input vector, and the offset vector is represented by η, the following formula gives the calculation formula of the fully connected layer:

$$b = Qa + \eta \tag{17}$$

The output of the fully connected layer needs to be processed by *softmax* function to realize the probabilistic classification of learning effect. Assuming that the *i*-th element in the vector is represented by U_i, the following formula gives the *softmax* function formula as follows:

$$R_i = \frac{p^{U_i}}{\sum_j p^{U_j}} \tag{18}$$

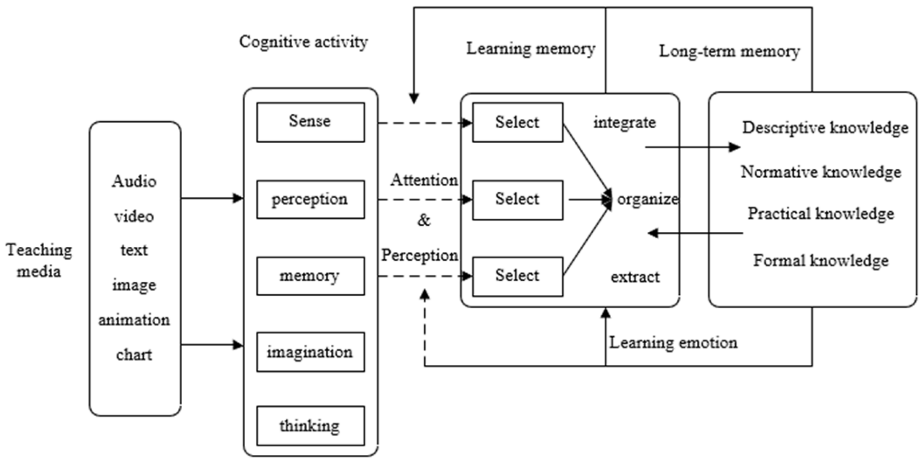

Fig. 2. Learning emotion theory in online learning process

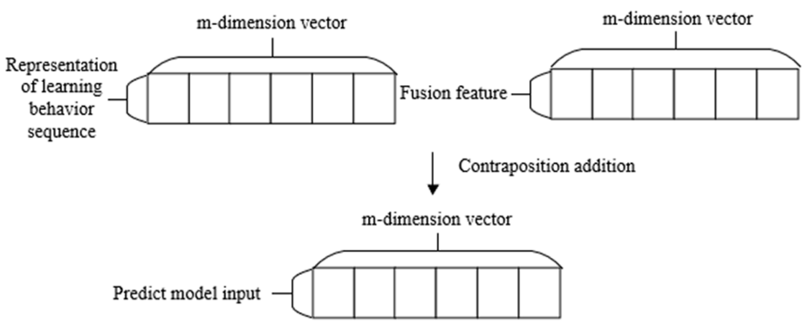

Fig. 3. Fusion feature vector generation process

4 Experimental results and analysis

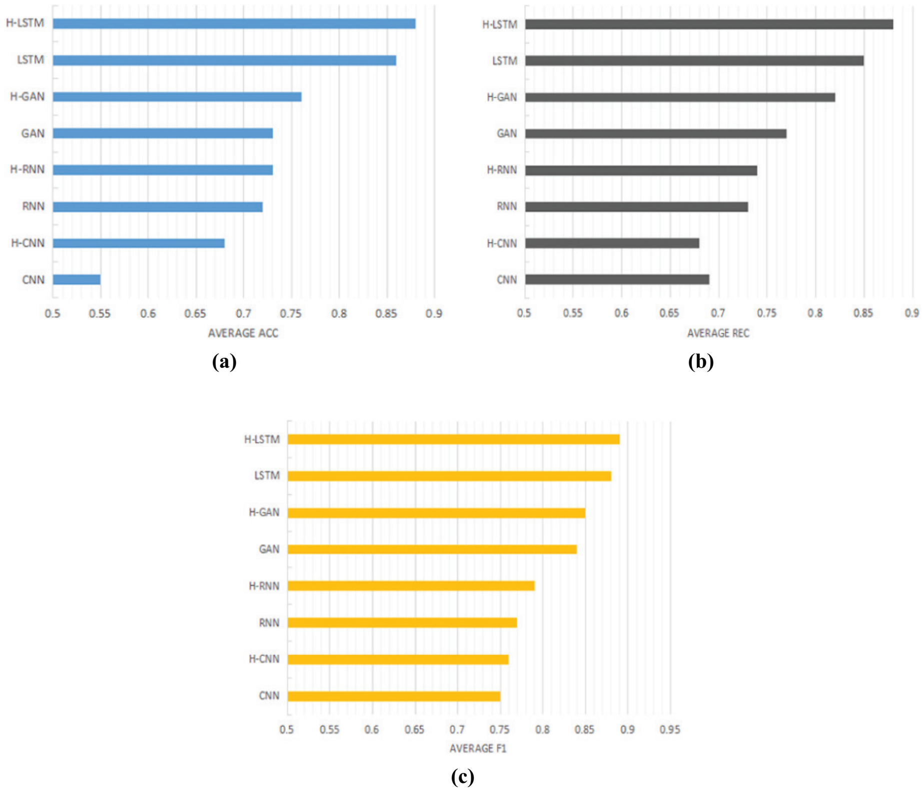

Fig. 4. Performance comparison of learning effect prediction under different indicators

The learning effect scale used in this article based on the learning participation under the influence of different learning emotions has high internal consistency, so the total score of learning effect is used for regression analysis, and the regression analysis results are given in Table 1. Assuming that learning satisfaction, learning self-confidence, learning interest and learning engagement are four independent variables that represent positive learning emotions, they have a significant correlation with learning effects, and the explanations are 3.5%, 2.7%, 8.2% and 24.9% respectively, indicating that four independent variables have a positive predictive effect on learning effects.

The main reason why Hawkes process is integrated into the prediction model of college students' classroom learning effect is to fully consider the influence of learning behaviors under the influence of different learning emotions on learning effect, so as to effectively identify students whose learning effect is not ideal due to negative learning emotions in the future learning process. In this article, training set and test set are constructed for training and performance evaluation of prediction model respectively. The models involved in performance comparison include *CNN*, *RNN*, *GAN* and *LSTM* models, as well as *H-CNN*, *H-RNN*, *H-GAN* and *H-LSTM* models combined with analysis results of learning behavior sequence represented by Hawkes process. The performance comparison results of learning effect prediction under different indicators are given in Figure 4. It can be seen from the figure that *H-LSTM* has the best learning performance, and the *ACC*, *REC* and *F*13 performance indexes of *H-LSTM* model are 0.88, 0.84 and 0.89 respectively, which are obviously improved compared with other models. This article verifies the representation of the students' learning behavior sequence based on the Hawkes process, which, combined with the characteristic information of students themselves and the courses they have learned, is effective in predicting learning effect.

After the completion of learning effect prediction, this article conducts positive emotion guidance to the students participating in the experiment, and further verifies the positive effect of positive emotion on learning effect through the experiment. Before and after positive emotion guidance, the students in the experimental group and the control group are tested by using the learning effect scale based on learning participation under the influence of different learning emotions. Table 2 shows the significance test results of each factor of positive emotion guidance in experimental group and control group. From the table, we can see that there is no obvious difference in learning effect between the experimental group and the control group before positive emotion guidance, but the experimental group after positive emotion guidance has a large increase rate in learning effect, with obviously improved positive effect.

Table 1. Regression analysis of positive emotions on learning effect

Dependent Variable	Independent Variable	B	β	R^2	I
Learning effect	Learning satisfaction	0.362	0.162	0.024	2.369**
	Learning self-confidence	0.417	0.137	0.069	3.274*
	Learning interest	0.958	0.281	0.037	4.512***
	Learning engagement	1.2053	0.539	0.241	13.629*

Table 2. Significance test of positive emotion guiding factors in experimental group and control group

Factors	Experimental Group		Control Group		T-value
	M	SD	M	SD	
Learning satisfaction	23.527	8.269	36.292	6.291	33.528
Learning self-confidence	55.162	13.527	42.518	13.284	42.157
Learning interest	31.274	7.402	33.471	7.632	40.215
Learning engagement	39.852	7.629	25.418	6.241	43.629
Total average score of positive emotion	13.627	4.352	13.629	4.295	35.284
Total average score of learning effect	37.541	7.169	38.274	6.392	52.483

Table 3. Analysis of the difference between positive group and negative group in post-test scores

	Positive Group (30 Students)	**Negative Group (30 Students)**	**T**	**D**
	M (SD)	**M (SD)**		
Learning satisfaction	35.26 (9.142)	31.26 (12.584)	2.304**	0.638
Learning self-confidence	3.52 (1.597)	4.29 (1.302)	–2.639*	0.742
Learning interest	5.29 (1.309)	5.74 (1.941)	–1.204*	0.398
Learning engagement	5.284 (1.047)	3.62 (1.304)	2.639*	0.835
Comprehension test	13.628 (4.382)	13.34 (4.825)	1.204	0.417
Transfer test	5.62 (2.485)	3.61 (2.596)	2.374**	0.629

Note: $*P < 0.05$,$**P < 0.01$.

Finally, this article uses SPSS20.0 to analyze the sample data of the test set. In terms of different types of emotional states of students' classroom learning, Table 3 shows the mean and standard deviation of emotional quantification and post-test achievement quantification of students in positive learning emotion group and negative learning emotion group. The difference analysis shows that there is no significant difference in the baseline weight of positive learning emotion and negative learning emotion between the two groups, but there is obvious difference in the post-test scores, which further verifies the positive effect of positive emotion on learning effect.

5 Conclusion

This article fully considers the positive learning emotion, and makes a research on the prediction of college students' classroom learning effect. Firstly, this article defines the behavior data of students in the online learning process based on learning emotions, and studies the correlation between college students' classroom learning behaviors based on Hawkes process. Then, based on the learning participation under the influence of different learning emotions, the online learning effect of students is quantified, and the prediction model of students' classroom learning is constructed by combining the learning behavior sequence analysis results represented by Hawkes process and the characteristic information of students themselves and courses. Combined with the experiment, the regression analysis is carried out by using the total score of learning effect, and the corresponding regression analysis results are given. The performance comparison of learning effect prediction under different indicators is completed. This article verifies the representation of the students' learning behavior sequence based on the Hawkes process, which, combined with the characteristic information of students themselves and the courses they have learned, is effective in predicting learning effect. The significance test results of each factor of positive emotion guidance between experimental group and control group and the difference analysis results of post-test scores between positive group and negative group are given to further verify the positive effect of positive emotion on learning effect.

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