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E-learning Learning Behavior Evaluation and Prediction Method Based on Sentiment Analysis

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Abstract. The full name of E-learning is Electronic Learning, which refers to an online learning model that realizes the feasibility of learning at various times and on multiple occasions and provides learners with many learning resources. This paper aims to research and analyze E-learning learners' learning behavior and recommend more appropriate courses to them by evaluating and predicting their learning behavior to improve the efficiency of E-learning learning. Therefore, when studying the evaluation and prediction method of E-learning learning behavior, this paper introduced sentiment analysis technology, constructed an E-learning learning behavior evaluation and prediction model based on sentiment analysis, and compared it with another commonly used evaluation model. The experimental results showed that the average accuracy of the Markov model's learning behavior evaluation was higher than 80%, the highest average accuracy of prediction was 81%, and the lowest value was only 69%; the E-learning learning behavior evaluation and prediction model based on sentiment analysis had an average accuracy of more than 80% in the assessment and prediction of online learning behavior.

Keywords: Emotion Analysis, E-learning Learning Behavior, Markov Model, Prediction Accuracy
DOI: https://doi.org/10.14733/cadaps.2024.S22.236-250

1 INTRODUCTION

In recent years, information technology has developed rapidly. Now, people are in the era of big data. The teaching model has been dramatically reformed to realize the combination of learning classroom and information technology; the emerging E-learning learning model has been continuously developed and improved. Compared with the traditional face-to-face classroom teaching model, E-learning has more advantages. In the learning process, learning behavior evaluation plays an important role. Practical learning behavior evaluation can help the teacher to have a good understanding of the learner's learning situation and to make corresponding teaching measures so that the learner can learn more efficiently and be more involved in it. However, some things could be improved in the current E-learning learning environment. Due to the lack of face-to-face realistic communication between teachers and students, it is impossible to accept and deal with learners' feedback and learning behavior changes promptly, and the various problems of learners in the online learning process cannot be well dealt with, which results in the low learning efficiency of e-learning. Therefore, how to scientifically and effectively obtain feedback on students' learning behavior in E-learning learning and make predictions and recommendations based on this feedback has become a significant research direction.

Since the rise of the E-learning learning model, it has been continuously developed and perfected, and many scholars have carried out related research on this learning model. Nihuka K A researched and investigated the impact of collaborative curriculum design on teachers' professional learning at the Open University of Tanzania (OUT) in designing and delivering e-learning courses. The experimental results showed that teachers are satisfied with the collaborative online course design, and this strategy is helpful for their professional learning [13]. To examine the factors influencing overall employee acceptance, satisfaction, and future use of e-learning, Fleming J developed an online survey and invited employees from an Australian railway organization to participate; the findings suggested that age is not a significant factor influencing future use intentions or satisfaction with e-learning, although people often support stereotypes [2]. Based on the social exchange theory, Luo N studied understanding how interaction affects students' sense of community and willingness to continue using e-learning platforms; the experimental results showed that student-teacher interaction and student-student interaction significantly enhanced students' membership awareness and influence, which in turn increased their stickiness to the e-learning platform [9]. Lai H J discussed the current state of information literacy, self-directed learning readiness, and e-learning attitudes among public librarians; the findings suggested that public librarians' perceptions of information literacy, self-directed learning readiness, and attitudes towards e-learning are positive. Information evaluation was the strongest predictor of public librarians' attitudes toward online learning, followed by creative learning, love of learning, and self-directed learning [6]. Many scholars have studied the E-learning learning model, but there are still many gaps in its learning behavior evaluation and prediction methods. Based on this, emotion analysis technology will be introduced when studying the evaluation and prediction methods of e-learning learning behavior.

Sentiment analysis technology is an integral part of the field of natural language, which has been widely used since a very early time, and related research on sentiment analysis is also emerging one after another. Wang Z proposed a joint factor graph model to learn monolingual and bilingual information from each post for exploring the relationship between different emotions and used the belief propagation algorithm to understand and predict the model; the empirical studies demonstrated the importance of sentiment analysis in code-switched texts and the effectiveness of the proposed joint learning model [19]. To predict the common sentiment among people from different locations during the COVID-19 lockdown, Amsaprabhaa M proposed an optimized Latent Dirichlet Allocation (LDA) method for finding the best hyperparameters using grid search, the experimental results demonstrated that the proposed LDA model - using grid search as well as RNN model for sentiment classification outperforms other state-of-the-art methods [1]. Jiang H combined facial expressions and EEG to establish three different models for recognizing multimodal fusion emotions; the results showed that expression patterns helped eliminate EEG signals containing little or no emotional features and that adding facial expressions affected EEG features to a certain extent [3]. Kottursamy K discussed various standard deep learning algorithms for emotion recognition and adopted a novel convolutional neural network (CNN) called eXnet to build a new CNN model that utilizes parallel feature extraction; the experimental results showed that this method adopted an effective method to reduce overfitting while keeping the overall size within a controllable range [5].

When studying the evaluation and prediction method of E-learning learning behavior, this paper introduced sentiment analysis technology, constructed an E-learning learning behavior evaluation and prediction model based on sentiment analysis, and compared it with the hidden Markov model. The experimental results showed that the judgment accuracy of E-learning learning behavior was consistent with the Markov model, which was more than 80%, and the correct recognition rate of learning behavior was also high. In predicting learning behavior, the prediction accuracy of the sentiment analysis model was above 80%. In contrast, the prediction effect of the Markov model was relatively poor, the highest being 81% and the lowest being 69%. The comparison showed that the algorithm based on sentiment analysis can not only accurately identify the learning behavior of E-learning but also predict the results more accurately, which is very suitable for studying E-learning learning behavior.

2 E-LEARNING LEARNING BEHAVIOR EVALUATION AND PREDICTION METHOD

2.1 E-learning Related Theoretical Basis

2.1.1 Basic Concepts

E-learning refers to a teaching model of online learning. There are many teaching forms. Compared with the traditional teaching model, E-learning has more advantages in interactivity and shared resources between teachers and students [4]. A comprehensive analysis of the various learning forms of E-learning showed that all forms of this education model have two things in common: computer and learning, and the current research on E-learning mainly included three aspects: technical support, learners, and educational services.

2.1.2 The Connotation of Learning Behavior

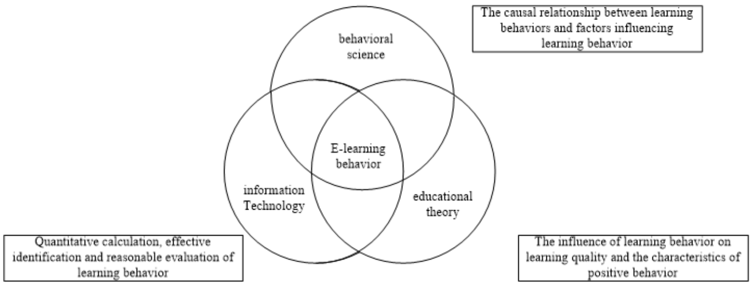

Figure 1: The logical connotation of E-learning learning behavior.

As shown in Figure 1, the research content of the educational theory is that the learning effect was affected by the behavior of the students themselves, and the characteristics of positive influence will be analyzed at the same time; the research content of information technology is the quantification of learning behavior in the process of online learning mode; the behavioral science research was related to factors affecting learning behavior.

2.1.3 Characteristics of Learning Behavior

The learning behavior produced by the learners of the E-learning learning mode in the learning process has the following main characteristics:

1. Study Time is Optional

Generally speaking, the learning mode of E-learning does not impose compulsory education on learners, which is very different from the standardized education method. In addition, learners in this mode learn voluntarily and spontaneously. Usually, the content of learning is mainly what the learners are interested in, and there is no fixed learning arrangement. Therefore, E-learning students typically have different learning arrangements, and the learning time showed a decentralization trend [11].

2. Termination of the Course

For the E-learning learning mode, most of the students' learning was autonomous learning, and their learning behavior was easily affected by the interference of external factors. In addition, relevant research showed that more than 50% of learners will stop learning when online learning is interrupted. Therefore, the learning mode of E-learning has the characteristics of being interrupted at any time.

3. Surprise Learning

Some scholars conducted a statistical analysis on the completion of an E-learning classroom in a research survey and found that more than 75% of the students who can complete the class were concentrated in 1-2 days to complete the class, which showed the sudden concentration of the E-learning course.

Due to several characteristics of E-learning curriculum learning, learners have different learning performances in online learning classrooms, and learners in these other learning states can be classified, as shown in Table 1.

category	*Behavioral characteristics*
Auditing	*Participate in coursework but rarely participate in discussions and comments.*
Completing	*Watch most of the lessons and participate in most of the assignments.*
Disengaging	*Appears only at the beginning of the course*
Sampling	*Participate in coursework only at different stages of the course.*

Table 1: E-learning learner classification.

Among the four types of learners, only "completers" and "auditors" can complete the E-learning class, but "completers" are more active in course interaction than "auditors." The main problem groups in the learning model of E-learning courses are "disengagers" and "samplers," and there is a high course dropout rate among these two types of learners. However, the latest research showed that the learning benefits obtained by "samplers" from E-learning courses were also non-growth, and they can also improve their academic standards.

2.2 Sentiment Algorithm Model

2.2.1 Basic Concepts

Sentiment analysis technology uses computers to analyze and process the emotional attitudes contained in sentences and classify different emotional attitudes, which has excellent research value [10]. The purpose of sentiment analysis is to analyze the emotional attitude of objective things. According to the text level, sentiment analysis can be stratified from high to low, namely word, sentence, and chapter levels. As one of the essential branches of natural language processing, sentiment analysis technology is widely used in the current computer field [14], and many classic Internet applications were born, such as personalized education, effect evaluation, behavior prediction, etc. The technology can understand deep insights and process the information collected flexibly.

2.2.2 Construction of E-learning Learning Behavior Evaluation and Prediction Model Based on Sentiment Analysis

The E-learning learning behavior evaluation and prediction model based on sentiment analysis constructed in this paper applied the FGMSAM model, and the behavior prediction and course recommendation algorithm based on sentiment change trend (SBPCRA algorithm for short), and these two technologies were described.

1. Behavior Prediction Recommendation Model

This paper proposed the SBPCRA algorithm for predicting E-learning learning behavior. This model aims to fit the learning behavior relationship between the student's academic situation and emotional characteristics through the small-batch gradient descent method and then infer the possibility of students' graduation in the E-learning course. In this way, suitable courses can be recommended to students with a meager graduation rate of E-learning courses to improve the graduation rate. The first step of the recommendation model is to aggregate the sample data according to the similarity clustering method and then obtain the graduation rate of the corresponding students. Then, a multiple linear regression equation is established [18], and a small amount of gradient descent is used to obtain the optimal partial regression coefficient combination to realize the model's training [12]. The SBPCRA model in this paper can be divided into two sub-modules: the learning behavior prediction model and the course recommendation model for predicting the results. Both have a clear division of labor and serve the SBPCRA model. The detailed flow chart of the model can be seen in Figure 2.

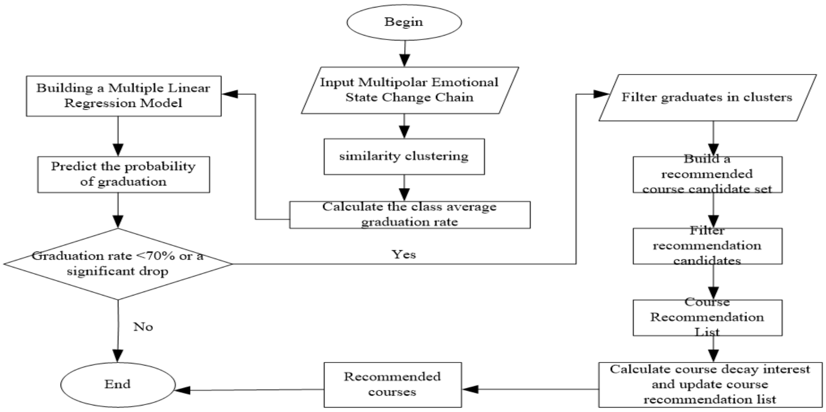

Figure 2: SBPCRA algorithm recommendation model.

2. Learning Behavior Evaluation Model

The student's emotional multi-polarity assessment must deepen the understanding of e-learning learners' behavioral learning. Therefore, in response to the research needs of this paper, the FGMSAM model [15] was proposed. The text processing steps of this model are as follows.

Text merge. Before evaluating the staged emotional characteristics of E-learning students, it is necessary to merge texts. The merged content is the text data of discussions, questions, answers, and comments under the same class time t, and a segment set is established according to the time length T. The expression is:

$$\mathrm{U}(\mathrm{K_n}flat) = \{\mathrm{prgh_1}, \mathrm{prgh_2}, \cdots, \mathrm{prgh_t}, \cdots \mathrm{prgh_T}\} \tag{1}$$

In the Formula (1): Kn——the n-th learner;

U(Kn)——the segment set of the nth learner;

Prght——the combined paragraphs of discussion, questions, and answers, comment texts of the nth scholar in the t-th session;

T - the length of the class.

Paragraph clauses. According to the usual text habits, prgh1 is segmented, and the corresponding sentence set Q(prgh1) is constructed simultaneously. The expression is:

$$\mathrm{Q}(\mathrm{prgh_t}) = \left\{\mathrm{stat_1}, \mathrm{stat_2}, \cdots, \mathrm{stat_m}, \cdots, \mathrm{stat_{NQ}}\right\} \tag{2}$$

In the Formula (2): Q(right)——the sentence set of the segment right;

Statm——the m-th statement in segment prght;

NQ——the length of the statement set Q(prght).

Split words and remove stop words. Used the IKAnalyzer system for word segmentation, added multiple sentiment dictionary resources to the user word segmentation dictionary, deleted the stop words after word segmentation, and got the sentence vector. The calculation is:

$$\mathrm{Vctr}(\mathrm{stat_m}) = \{\mathrm{word_1}, \mathrm{word_2}, \cdots, \mathrm{word}_{\ \mathrm{n}}, \cdots, \mathrm{word_{NV}}\} \tag{3}$$

In the Formula (3): Vctr(statm)——the word vector of the statement statm;

Wordn——the n-th word in the statement statm;

NV——the length of the word vector Vctr(statm).

Emotional word matching. Judging the word vector Vctr(statm), if the inspirational word is successfully matched, go to the next step; if no emotional word is reached, continue to check the next-level word vector.

Modifier matches. Used part-of-speech dictionaries such as degree adverbs to match sentiment modifiers and stored a series of words and punctuation marks in the density sentiment word vector according to the relationship between positions. The expression is:

$$\mathrm{Vctr}_{\mathrm{Sent}(\mathrm{stat_m})} = \left\{\mathrm{W_m}, \mathrm{E_l}, \cdots, \mathrm{M_i}, \mathrm{R_j}, \cdots, \mathrm{U}, \mathrm{F}, \mathrm{O}\right\} \tag{4}$$

In the Formula (4): Vctr_Sent(statm)——the density sentiment word vector of the sentence statm;

Wm——the m-th emotional word in the statement statm;

El——the l-th degree adverb in the statement statm;

U——negative adverb in the statement statm;

F——the transitional conjunction in the statement statm;

Q——progressive conjunction in the statement statm;

Mi——the i-th emotional symbol in the statement statm;

Rj——the j-th emotional punctuation mark in the sentence statm.

Repeated steps a, b, c, d, and e until all students were completed.

3. E-learning Learning Behavior Evaluation and Prediction Model Based on Sentiment Analysis

The overall E-learning learning behavior evaluation and prediction model combines the above sentiment, the analysis-based SBPCRA algorithm prediction and recommendation model, and the FGMSAM evaluation model. The comprehensive E-learning learning behavior evaluation and prediction model in this paper can be seen in Figure 3.

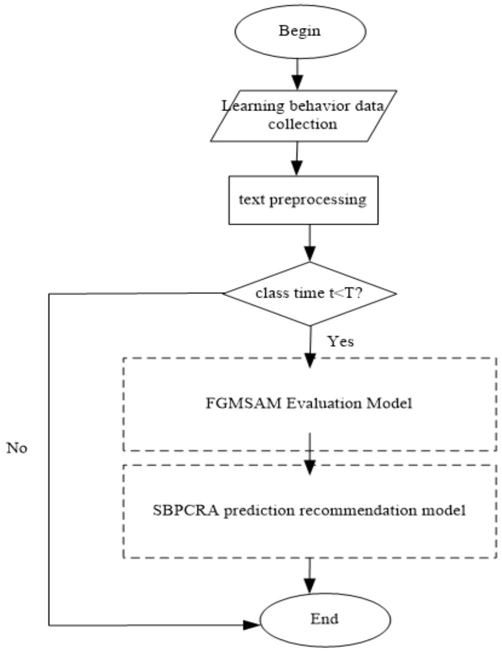

Figure 3: E-learning learning behavior evaluation and prediction process based on sentiment analysis.

The model first analyzed and processed the collected data information and discriminated the E-learning online courses. The data is input into the evaluation model if the course is not over. After the evaluation, it is further input into the prediction recommendation model to obtain the prediction and recommendation courses. On the contrary, if the course has been completed, it will end directly without participating in the model operation.

Then, the input data was multi-polarized through the FGMSAM model, and the students' emotions were analyzed and quantitatively evaluated. Next, it was necessary to judge the progress of the E-learning course and what stage it was in. Calculate the students' dominant emotions stage if the course is still ongoing. At the same time, the trend analysis of the emotional changes of the students of the E-learning course was carried out, and the corresponding dynamic change chain of the students was obtained by processing and analysis so that the emotional bias of the students of the E-learning course can be judged. The output dynamic change chain was input into the next-level model.

Finally, it was the operation of the SBPCRA prediction recommendation model. After receiving the emotional change chain data, the students with similar emotions were classified and aggregated, and the average graduation rate of different categories was calculated to establish a corresponding multivariate linear model; the subsequent graduation probability can be predicted through the solution of the model. Then, the graduation probability of the students of the E-learning course was judged. If the probability is high, the calculation will be withdrawn; if it is low, it will be further screened. Then, the second screening will be carried out according to the filtering criteria, and then the E-learning course recommendation table will be generated. After the recommendation table was developed, it can be continuously updated according to the changes in students' interests and the degree of participation in the E-learning course. This way, the evaluation and prediction model of E-learning learning behavior based on sentiment analysis was completed.

2.3 Evaluation of E-Learning Learning Behavior Based on Hidden Markov Model

2.3.1 Model Definition

The operation process of the hidden Markov model has double random properties, in which there are two random variables: one is the Markov chain, which is invisible [8], and the transition probability can describe the transition of the state; there is also a random sequence, which can be observed, and the relationship between the observed value and the state is usually described by the probability of the observed value. The model is represented as:

$$\alpha = \{S, V, C, D, \pi\} \tag{5}$$

In the Formula (5): S——hidden state set;

V——set of observation symbols;

C——state transition probability matrix;

D——the observed symbol probability distribution of the state;

π ——The probability distribution of the initial state.

2.3.2 Application of the Model

Assumed that the observation sequence is R={r1，r2，…， rt} and the model α, then the Markov model mainly solved two problems in the study of E-learning learning behavior in this paper: one is the evaluation of E-learning learning behavior; the other One is the learning problem. The α parameter is adjusted by the Baum-Welch algorithm to maximize the conditional probability [16]. The algorithm process is:

1. Define forward variables:

$$\beta_t(n) = P(r_1 \cdots r_t, q_t = s_n)|\alpha \tag{6}$$

On the premise that the model α is determined, a partial observation sequence （r1，r2，…， rt） will be generated at time t, and sn is the current state probability. The forward variable can be iteratively calculated by Formula (7):

$$\beta_{t+1}(m) = \left(\sum_{n=1}^{I} \beta_t(n)\beta_{nm}\right)d_t(r_{t+1}) \tag{7}$$

In the Formula (7), $1 \le m \le I; t = 1,2,\cdots, T-1; \beta_1(n) = \pi_n d_n(r_1)$.

2. Backward variables:

$$\gamma_t(n) = P(r_{t+1} \cdots r_T | q_t = s_n, \alpha) \tag{8}$$

The backward variables refer to the sn state;under the condition of time t, from time t+1 to the final observation sequence probability, the backward variable can be iteratively calculated by Formula (9):

$$\gamma_t(n) = \sum_{m=1}^{I} \beta_{nm} d_m(r_{t+1}) \beta_{nm}(m) \tag{9}$$

In the Formula (9), $1 \le n \le I; t = T-1, T-2 \cdots 1; \beta_T(n) = 1$.

3. Output probability:

$$P(R|\beta) = \sum_{n=1}^{I} \beta_t(n)\gamma_t(n)\; 1 \le t \le T \tag{10}$$

4. The probability of sm at time t+1:

$$\delta(n, m) = P(q_t = s_n, q_{t+1} = s_m | R, \alpha) \tag{11}$$

5. The probability that the state is sn at time t:

$$\theta_t(n) = P(q_t = s_n | R, \alpha) = \frac{\beta_t(n)\gamma_t(n)}{\sum_{n=1}^{I} \beta_t(n)\gamma_t(n)} \tag{12}$$

6. The ratio of the state transition between sn and sm to the expected number of states n transitions:

$$\bar{c}_{nm} = \frac{\sum_{t=1}^{T-1} \rho(n,m)}{\sum_{t=1}^{T-1} \theta_t(n)} \tag{13}$$

7. The ratio of the expected number of observed symbols for the UK to the sm state in the sm state:

$$\bar{d}_m(k) = \frac{\left(\sum_{t=1, r_t=u_k}^{T} \theta_t(m)\right)}{\sum_{t=1}^{T} \theta_t(m)} \tag{14}$$

8. The probability of state sn at t=1:

$$\bar{\pi} = \theta_1(n) \tag{15}$$

From Formula (15), Formula (13), and Formula (14), $\bar{\pi}$, $\bar{c}_{nm}$, and $\bar{d}_m(k)$ can be obtained; these three parameters formed a new model α1. The newly acquired model was brought back into the above calculation model, and the iterative calculation was repeated repeatedly until the output parameters showed a convergence trend to get the optimal parameters of the hidden Markov model [17].

After obtaining the relevant parameters, a hidden Markov model was established to evaluate the student's learning behavior in the E-learning course. According to the student's learning behaviors, they were comprehensively classified, the learning behaviors of each type of student were predicted, and the corresponding E-learning learning courses were recommended to improve the learning efficiency of E-learning courses effectively.

3 EVALUATION AND PREDICTION EXPERIMENTAL VERIFICATION

To verify the scientific accuracy of the E-learning learning behavior evaluation and prediction model based on sentiment analysis established in this paper, the experiment selected 1000 E-learning learners as the research objects, collected their learning data information, and used the evaluation prediction model based on sentiment analysis and the evaluation prediction model based on hidden Markov to evaluate and predict the learning behavior of E-learning learners. At the same time, the actual learning situation was compared, and the accuracy of the E-learning learning behavior prediction of the two models was observed. The experimental process and data are as follows.

3.1 Evaluation and Prediction Model Based on Sentiment

3.1.1 Evaluation of Learning Behavior Based on Sentiment Analysis

The emotional types of the 1000 learners in the E-learning course were evaluated and analyzed by the FGMSAM evaluation model based on the sentiment analysis mentioned above. The data related to emotions, such as happiness, sadness, anger, etc., were counted, and the specific statistical data were shown in Table 2.

emotional orientation	*Number of learners*	*proportion of the population*	*Number of graduate learners*	*average graduation rate*
happiness	*250*	*25%*	*32*	*12.8%*
surprise	*252*	*25.2%*	*35*	*13.9%*
expectations	*265*	*26.5%*	*16*	*6.0%*
trust	*122*	*12.2%*	*6*	*4.9%*
anger	*45*	*4.5%*	*2*	*2.1%*
sad	*41*	*4.1%*	*2*	*1.5%*
fear	*25*	*2.5%*	*1*	*0.9%*
disgust	*14*	*1.4%*	*1*	*0.05%*

Table 2: Learner's emotional tendency analysis table.

It can be seen from Table 2 that among the students of the E-learning course, the emotions of happiness and surprise were the largest, accounting for 25% and 25.2% of the total number of students, respectively. However, the students whose emotions were pleasantly surprised had the highest graduation rate. The average graduation rate reached 13.9%, and the number of graduates reached 35. It was thus known that when learning E-learning online courses, people with happy and surprising emotions are more likely to complete the entire online course study. Therefore, when conducting E-learning studies, we recommend more online courses to make learners feel happy and surprised and have other positive emotions. The negative emotions of students with emotions such as anger, sadness, and fear accounted for a relatively small proportion of the total number of students, accounting for 4.5%, 4.1%, and 2.5%. The E-learning courses selected in this experiment had a relatively high degree of learner acceptance. At the same time, it can also be found that when E-learning learners have negative emotions about the course, the student's average graduation rate becomes very low, and disgusted students can hardly complete the course. Therefore, when conducting E-learning studies, it was necessary to investigate learners with negative emotions, find reasons, and recommend more suitable online learning courses to students.

The emotion data obtained through the questionnaire was compared to verify the model's emotion recognition effect. The comparison of the two groups of data is shown in Figure 4.

As can be seen from Figure 4, the emotional evaluation results of the E-learning learners by the FGMSAM evaluation model based on emotion analysis were close to the emotional state of the students obtained by the questionnaire, which indicated that the evaluation model has a high degree of recognition accuracy. However, a detailed analysis of the data showed that among the sentiment assessments obtained by the model, the average graduation rate of positive emotions is generally higher than the actual results. In comparison, the average graduation rate of negative emotions is usually lower than the actual results.

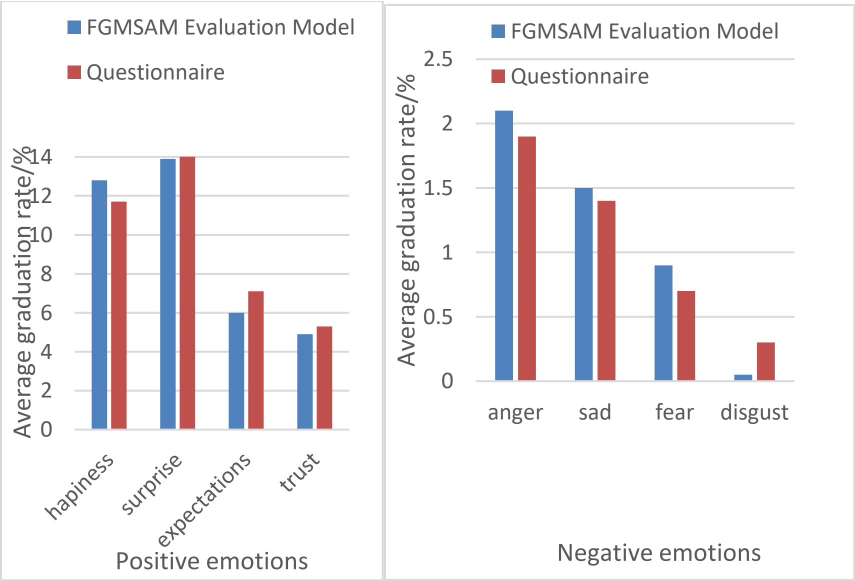

Figure 4: The average graduation rate of E-learning learners with different emotions.

3.1.2 Learning Behavior Prediction Based on Sentiment Analysis

The multi-emotional state data obtained by the evaluation model was input into the behavior prediction model based on emotion change (SBPCRA model), and then the relationship curve between emotional state change and graduation rate can be obtained by solving the curve model; we can predict the graduation probability of E-learning learners. In this experiment, the 1000 respondents were divided into four groups, four different E-learning courses were selected for all learners to learn, and the final learning situation was counted. Compared with the prediction results of the model, the results are shown in Figure 5.

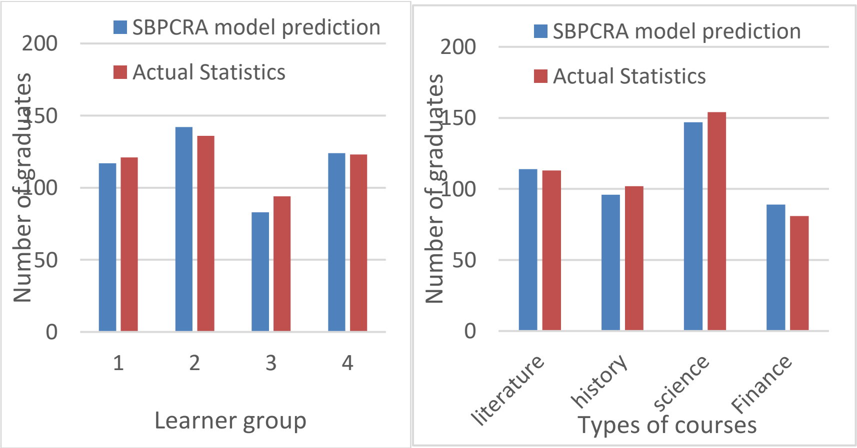

Figure 5: Graduation of E-learning learners.

It can be seen from Figure 5 that the prediction results of the SBPCRA model on E-learning learning behavior were closer to the actual situation. Among the 1,000 survey respondents, the e-learning courses with the worst completion status were History and Finance Online. In contrast, the science E-learning courses had the best completion status, with 154 people completing them. The learning behavior of E-learning was also significantly related to the course content. If this can be considered in the prediction system, the prediction accuracy of online learning behavior will be improved.

3.2 Evaluation and Prediction of E-Learning Learning Behavior Based on Hidden Markov Model

log P(W|λ)	*minimum*	*mean*	*maximum*
Plagiarism Collection	*-7.07*	*-7.17*	*-6.41*
benchmark set	*-11.92*	*-10.35*	*-9.38*
anomaly set	*-14.98*	*-13.89*	*-13.11*

Table 3: Comparison of each dataset sample's log P(W|λ).

Table 3 shows the online assignments of 1,000 E-learning learners; it can be seen that the plagiarism set was much larger than the average value of the standard set. The reason is that most E-learning learners choose to plagiarize online assignments, but the mean of the anomaly set was much smaller than that of the standard set, and the error feedback was more than that of the standard set.

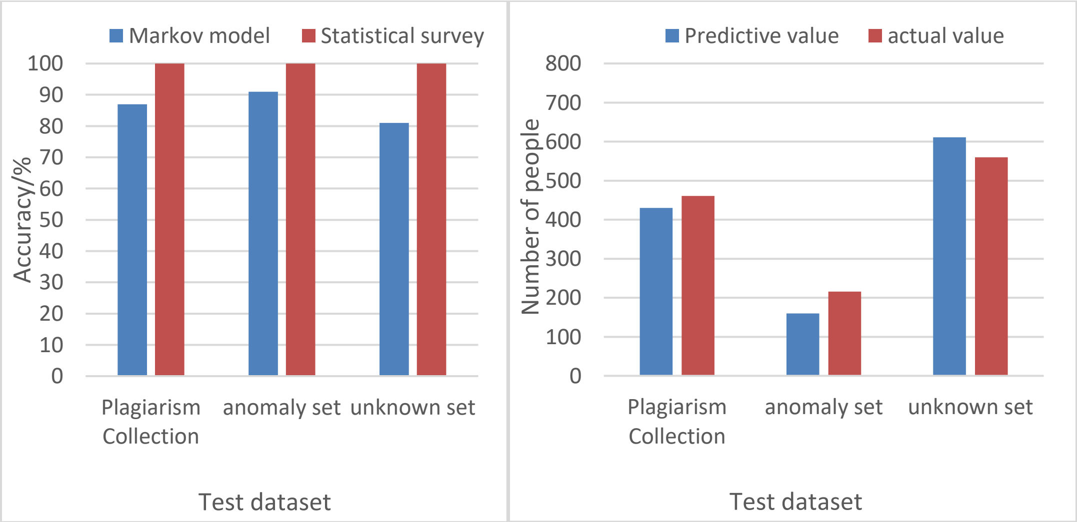

Figure 6: Learning behavior evaluation and prediction of Markov model.

Figure 6 compares E-learning learning behavior's evaluation and prediction results based on the Markov model and the survey results. The accuracy rate of the statistical survey is 100%; that is, taking the results of the statistical survey as the existing standard, it can be seen that the correct rate of the model's evaluation of learning behavior and the actual result was at most 19%. The difference between the predicted results of learning behaviors and the actual results was 61 people, and they all appeared in the unknown set because the strange behaviors were more challenging to predict.

3.3 Comparison of the Accuracy of the Two Models

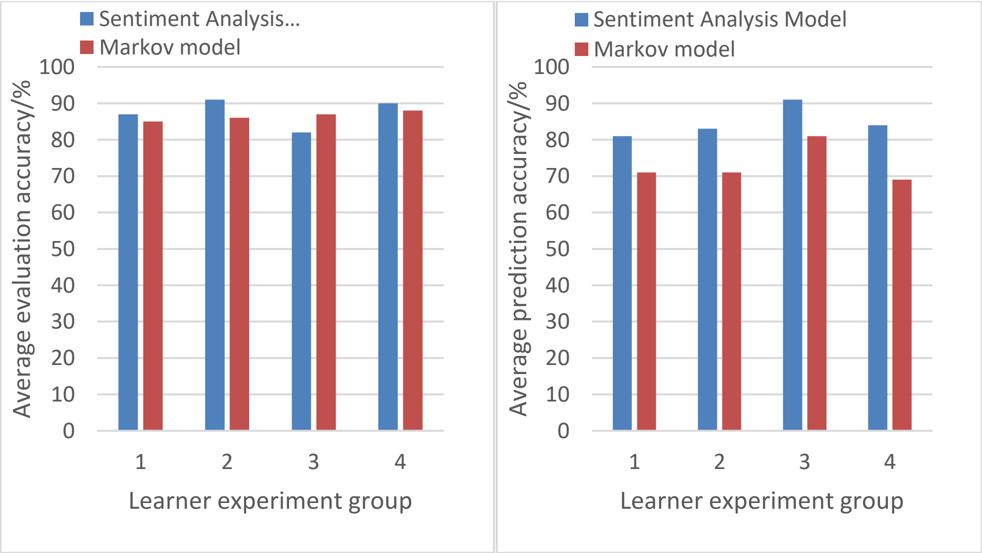

Figure 7: E-learning learning behavior evaluation and prediction accuracy.

According to the analysis results of the E-learning learning behavior of the two models, the sentiment analysis model was almost the same as the Markov model in the accuracy of the E-learning learning behavior evaluation and recognition, and both exceeded 80%, with a high degree of correctness of learning behavior recognition. From the results of E-learning learning behavior prediction, the prediction accuracy of the sentiment analysis model was still higher than 80%. Still, the prediction efficiency of the Markov model was relatively low; the highest was only 81%, and the lowest was 69%. In contrast, the algorithm model based on sentiment analysis accurately identifies E-learning's learning behavior and has a more accurate prediction effect.

4 CONCLUSIONS

This paper introduced the E-learning learning course and the different learning behaviors of its learners and constructed an E-learning learning behavior evaluation and prediction model based on sentiment analysis to analyze its learning behavior. In the experimental part, the constructed sentiment analysis model and the Markov model were used to evaluate and predict the learning behavior of the selected respondents. The experimental results showed that the model method constructed in this paper has a high accuracy in assessing and predicting E-learning learning behavior and can recommend more suitable E-learning courses to learners, thereby significantly improving the learning efficiency of E-learning learning and promoting the further development of E-learning. However, some model shortcomings were also found in the experiments, and the model needed to consider these when predicting and recommending E-learning courses. Therefore, to further improve the learning effect of E-learning, the model needs to be further enhanced and developed in future research.

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