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SBPM Model for Analyzing Students' Learning Behavior Based on Fine Grained Emotion Analysis and Emotion Assessment

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Different students have different learning behaviors, and their attitudes towards learning are directly reflected in their learning behavior. To improve students' self-learning ability and enhance the teaching level of universities, this study constructs an emotional change trend evaluation model based on fine-grained emotion analysis technology during the learning process. Based on the output results of the model, predictive analysis is conducted on students' learning behavior. The results showed that the designed emotional evaluation model could achieve an accuracy of over 80% in analyzing the trend of students' emotional changes, and the calculation time was only about 15 seconds. The proposed student learning behavior prediction model could reduce the average percentage error to 0.15% when predicting and analyzing students' learning behavior. The proposed student learning behavior prediction model consistently maintained an F1 score above 0.95 and an accuracy rate of over 97% in predicting students' learning behavior. The research model can accurately analyze the emotional changes of students during the learning process and predict and analyze their learning behavior. Universities can correct students' learning behavior based on the output results of the model, effectively improving students' learning efficiency and enhancing the teaching level of universities.

Povzetek: Uveden je model SBPM za napovedovanje študentskega vedenja na podlagi podrobne analize čustev. Model dosega visoko natančnost in pomaga izboljšati učno učinkovitost ter prilagoditi pedagoške strategije univerz.

1 Introduction

The continuous advancement of educational technology has made the analysis and understanding of Students' Learning Behavior (SLB) increasingly important. By analyzing SLBs, teachers can understand each student's unique needs and learning styles, and design personalized learning plans and teaching strategies accordingly [1, 2]. Learning Behavior Analysis (LBA) can also help students understand their learning habits and efficiency, thereby encouraging them to adopt more effective learning strategies and cultivate their ability for self-directed learning. LBA can not only assist teachers and students but also provide data support for education administrators to make more informed decisions on resource allocation, curriculum design, and policy formulation [3, 4]. In recent years, educational and psychological research has gradually recognized that students' emotional states and behavioral patterns have a significant impact on their learning outcomes. By analyzing nonverbal signals such as students' language, facial expressions, and body language, it is possible to identify and understand students' emotional states in more detail. Understanding students' emotional states can help teachers understand their emotional changes promptly and provide a basis for adjusting teaching strategies [5, 6]. Traditional teaching methods and evaluation systems often fail to fully reflect students' learning status and needs. Fine-grained Sentiment Analysis (FGSA) is an advanced emotion recognition technique that focuses on identifying and understanding an individual's specific emotional state in a particular context. Therefore, to improve the quality of education and student learning outcomes, this study establishes a Sentiment-change-trend-based Behavioral Prediction Model (SBPM) based on the FGSA method to analyze SLB.

This study innovatively utilizes the FGSA method to construct a multi-polar emotion assessment model for analyzing students' emotional changes. Based on the analysis results of the model, an SBPM model is constructed to predict and analyze SLB. The main contribution is the design of a fine-grained multi-level sentiment evaluation model. Based on the results of this model, predicting and analyzing SLB can help educators and participants develop more efficient teaching and learning methods.

2 Related works

FGSA is an emerging emotion analysis technology. Luo et al. employed deep learning sentiment analysis to ascertain the experiences of diverse guests who had evaluated Chinese economy hotels. The location factor received the highest praise, while negative emotions were mostly focused on facility details. This study provided a new method for understanding customer experience and discussed the significance of management theory and practice [7]. Wang Y et al. proposed a method of automatically constructing a fine-grained sentiment dictionary to improve the performance of sentiment analysis. This dictionary achieved significantly better F1 scores in emotion and sentiment analysis on multiple datasets [8]. Zhu S et al. proposed a customer hearing system that combines sentiment analysis and redesign mechanisms to improve the accuracy of product redesign. The system enhanced accuracy through ontology and professional knowledge and has been successfully applied to smartphone cases, verifying its effectiveness and providing reliable product redesign strategies [9]. Wang Z et al. proposed the MiMuSA method to enhance the granularity and interpretability of sentiment analysis. This method imitated the process of human language comprehension and identified multiple types of emotions through a multi-level modular structure. MiMuSA outperformed existing methods in accuracy and F1 Score [10]. Zhang H et al. proposed a lightweight regression model that combines statistical distribution and autoencoder to improve fine-grained financial prosperity analysis. This model significantly outperformed the baseline in news and Weibo data, with low computational overhead, while emphasizing the importance of dictionary methods [11] (Table 1).

Table 1: Summary of surveys related to fine-grained sentiment analysis

Author	Achievement	Deficiency
Luo J et al.	Discussed the role of sentiment analysis in hotel management	Not considering the emotional impact of hotel services on customers
Wang Y et al.	Constructed a new fine-grained sentiment dictionary	The new dictionary has low universality and is only applicable to certain fields
Zhu S et al.	Optimized the design strategy of smartphones using customer sentiment analysis	Not considering the usage habits of different customers
Wang Z et al.	Improved interpretability of FGSA	Only focus on the interpretability of language sentiment analysis
Zhang H et al.	Established a fine-grained emotional financial analysis model	The sentiment dictionary used does not focus on emotions with small fluctuations

SLB can reflect students' learning status. Fan J et al. proposed a deep learning recommendation method based on a multi-attention mechanism to improve the MOOC learning experience and reduce dropout rates. This model could effectively analyze learning behavior and recommend personalized MOOCs, improving the interpretability of recommendations [12]. Ikawati Y et al. proposed a learning style prediction model based on the ensemble tree method by analyzing Moodle logs and ILS questionnaire data to improve the efficiency of e-learning and personalized teaching. This model significantly improved classification accuracy compared to the single tree model [13]. Wang J et al. proposed a comprehensive review and classification method using natural driving research combined with computer vision technology to study driver distraction and safety issues. This method effectively identified driver behavior and revealed technological gaps in future research [14]. Mizael T M et al. proposed four contributions from Brazilian researchers to explore the relationship between racial issues and behavioral analysis in Brazil. These contributions underscored the perils of racial bias, stereotypes, and systemic racism, as well as novel approaches to measuring bias. They also advocated for enhanced international collaboration [15]. Wilder D A et al. proposed the role of response effort as an independent variable in addressing target responses in behavioral analysis. Clinical applications could reduce bad behavior and increase ideal behavior, while organizational applications could improve safety and recovery efficiency. The impact mechanism and future research directions were discussed [16] (Table 2).

Table 2: Survey summary of learning behavior analysis

Author	Achievement	Deficiency
Fan J et al.	Established a MOOC recommendation model based on LBA	Not paying attention to the impact of emotional changes on SLB
Ikawati Y et al.	Established a learning style prediction model	Not paying attention to students' emotional changes
Wang J et al.	Established a behavior analysis model based on computer vision	Not paying attention to changes in target emotions
Mizael T M et al.	Established a behavior analysis model based on historical factors	Only focus on historical legacy factors
Wilder D	Corresponding behavior	Not considering the impact

A et al.	analysis models were established based on response efforts	of personal emotional factors on behavior

In summary, existing research is deficient in its consideration of emotional states and their impact on learning behavior. This deficiency results in an inability to fully reflect the true learning status and needs of students. Moreover, the limited universality and applicability of the dictionaries used in sentiment analysis limit the wide applicability of the analysis results. In addition, existing research often overlooks students' personal usage habits and multidimensional emotional analysis. This results in an inability to fully capture the subtleties of emotional fluctuations and a deficiency in the comprehensive analysis and forecasting of students' emotional trajectories. These restrictions have affected a deeper understanding and effective intervention of SLB. Accordingly, the study assesses students' multi-level emotional states by developing a multi-polar emotional dictionary and anticipates SLB states based on the assessment outcomes. This approach aims to facilitate more precise methods for examining students' emotional and behavioral patterns.

3 Construction of a SLB prediction model based on emotion analysis

3.1 Construction of student emotional assessment model based on FGSA

The construction of a student emotional assessment model is aimed at evaluating and analyzing the emotional state of students, and analyzing the trend of student emotional changes based on the results of students' multi-polar emotional assessment. FGSA can identify and distinguish subtle differences in human emotions. When using this method to construct a student emotion assessment model, it is necessary to build an emotion dictionary [17]. According to the natural emotion differentiation method, human emotional perception can be divided into eight basic emotions. Based on eight basic emotional feelings, scholars have constructed a multi-level emotional dictionary. However, when translated into other language dictionaries, this dictionary contains a large number of synonyms that cannot reflect emotional levels. Therefore, it is necessary to perform synonym matching and weighting on the dictionary. The synonym matching and weighting method for the designed dictionary is shown in Figure 1.

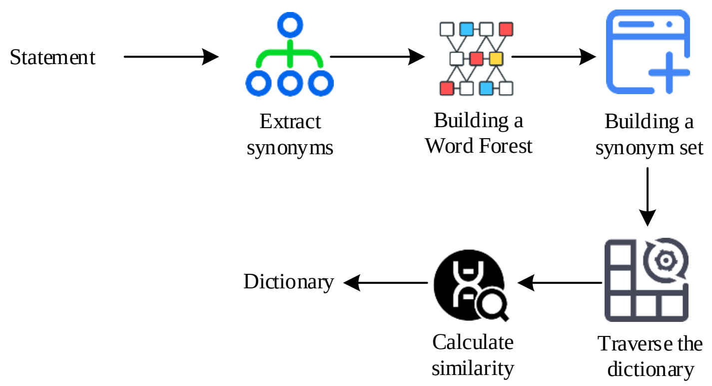


Figure 1: Dictionary synonym matching and empowerment process

The matching of synonyms is a fundamental step in building a multi-level emotion dictionary. The study chooses a synonym matching algorithm based on WordNet, which is a linguistic database that provides synonym relationships between words and a hierarchical structure of word meanings. When matching and weighting synonyms, it is necessary to calculate the similarity of word meanings. When calculating the similarity of word meanings, the first is to extract emotional words from the dictionary and use them as matching target words for synonyms. In the matching interval for extracting target words, some emotional words are selected to form a synonym set, and then the similarity between the extracted target words and the synonym set is calculated according to equation (1) [18, 19]. For the calculation of word meaning similarity, the cosine similarity algorithm is used in the study. Cosine similarity is a similarity measure that measures the angle between two non-zero vectors, suitable for distance calculation in high-dimensional spaces. The calculation of word meaning similarity comprehensively considers the similarity of word meanings and their structural distance in the dictionary. Through this method, synonyms can be more accurately identified and matched, providing a foundation for building a multi-level emotion dictionary.

$$sim\left(w_i, w_j\right) = m_l \cos\left(\frac{p \cdot \pi}{180}\right)\left(\frac{p-q+1}{p}\right) \tag{1}$$

In equation (1), p is the number of nodes contained in the first branch layer of synonyms. $sim(w_i, w_j)$ is the similarity between the target word and the matching word. q is the branch distance between the target word and the matching word in the first branch layer. The setting of this parameter reflects the emphasis on the distance factor in synonym similarity calculation. A smaller q value means a shorter distance, resulting in a higher similarity score. m_l is the similarity coefficient at the same level as the target word. The above operation is repeated until all sentiment words in the initial dictionary are traversed. Then, based on the similarity calculation results, the initial dictionary is divided into three different similarity subsets: high, medium, and low, as shown in equation (2).

$$\begin{cases} C(w_i, N)_g, & sim(w_i, w_j) \in [0.85,1] \\ C(w_i, N)_z, & sim(w_i, w_j) \in [0.65,0.85] \\ C(w_i, N)_d, & sim(w_i, w_j) \in [0,0.65] \end{cases} \quad (2)$$

In equation (2), $C(w_i, N)_g$ is a high similarity subset. $C(w_i, N)_z$ is a subset of medium similarity. $C(w_i, N)_d$ is a low similarity subset.

All elements in the high similarity subset are weighted to extract the emotional strength of the target word similarity. When setting the weights in the similarity subset, the coefficient is 0.85. The weight of the elements in the similarity subset is 0.85 times the weight of the extracted target word. The low similarity subset is directly deleted. Students' emotions during the learning process will constantly change as the course progresses. In the multi-polar sentiment dictionary, the emotional changes of students are shown in Figure 2.

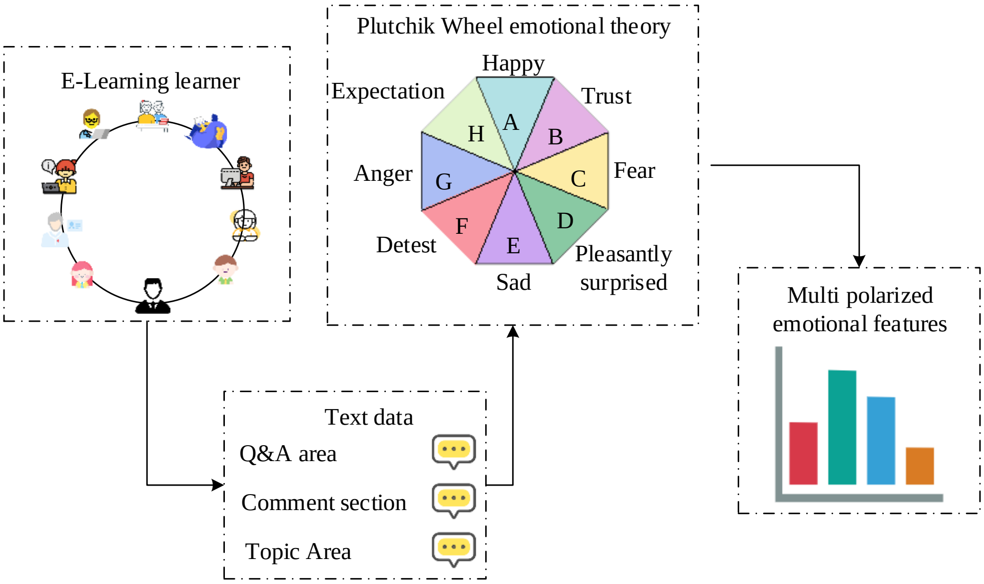


Figure 2: The emotional changes in different stages of learning

The data collection for FGSA mainly comes from text data of students' online Q&A and discussions. The preprocessing process first involves data cleaning, including merging text, constructing a set of language segments, and segmenting them according to the length of the course. Subsequently, the merged segments are subjected to sentence segmentation and word segmentation, and a sentence word vector is constructed after removing stop words. In terms of feature extraction, the study uses a multi-polar sentiment dictionary to match and modify sentiment words, while considering factors such as punctuation marks, sentiment word strength, emoticons, degree adverbs, negative words, transitional conjunctions, and progressive conjunctions. By calculating the quantitative value of sentiment strength in sentences, a multi-level sentiment vector is constructed to analyze students' emotional changes at different learning stages [20]. Data cleaning requires merging the text and constructing a set of segments based on different course levels, as shown in equation (3).

$$U(L_i) = \{prgh_1, \cdots, prgh_T\} \quad (3)$$

In equation (3), $U(L_i)$ is a set of language segments for a student. $prgh_T$ is the first student to participate in the discussion of text merging paragraphs in the course. T is the length of the course. After merging the texts, the paragraphs are divided according to equation (4).

$$S(prgh_t)=\{stat_1,\cdots,stat_j\} \quad (4)$$

In equation (4), $S(prgh_t)$ is the statement set. j is the statement index. After completing the sentence segmentation, the sentence is segmented and stop words are removed to construct a sentence word vector, as shown in equation (5).

$$V(stat_j)=\{word_1,\cdots,word_o\} \quad (5)$$

In equation (5), $V(stat_j)$ is a word vector. $word$ is a word. o is a word index. Finally, based on the multi-polar sentiment dictionary, sentiment words are matched and modified. After processing the raw data, the stage specific emotional intensity of students can be quantified based on their learning stage. The quantitative calculation of the emotional intensity of a statement is shown in equation (6).

$$p(stat_j)=\begin{cases}\sum_{o=1}^{O}\left(w_j\prod_{k=1}^{K}\varepsilon_k\mu+sym_{E\_fc}(\omega)+sym_{E\_fc}(\delta)\right)\sigma, & if \quad \sigma \quad appeared\\ \sum_{o=1}^{O}\left(w_j\prod_{k=1}^{K}\varepsilon_k\mu+sym_{E\_fc}(\omega)+sym_{E\_fc}(\delta)\right)\tau, & if \quad \tau \quad appeared\end{cases} \quad (6)$$

In equation (6), $p(stat_j)$ is the quantified value of emotional intensity. $sym_{E\_fc}(\delta)$ is the intensity of punctuation modification. w_j is the emotional intensity of emotional words. O is the number of sentiment words in the sentence. $sym_{E\_fc}(\omega)$ is the intensity of modification in emoticons. ε_k is the modifier strength of degree adverbs. μ represents the strength of negative word modification. σ is the modifying strength of transitional conjunctions. τ is the modifying strength of progressive conjunctions. The quantitative calculation of emotional intensity integrates various factors such as emotional words, facial expressions, and degree adverbs. The weight setting of each parameter is based on linguistic and psychological research to ensure accurate quantification of emotional intensity. According to equation (6), the multi-level emotion vector of students during the course hours can be calculated, as shown in Figure 3.

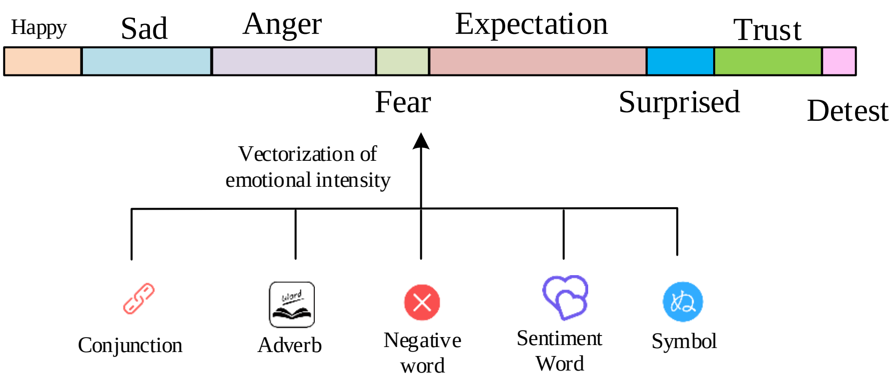


Figure 3: Phdic multi-level emotion vectorial representation of learners

Happiness and sadness, anger and tragedy, expectation and surprise, trust and disgust are four pairs of bidirectional emotions. If the calculation result of the sentence sentiment vector is negative, the corresponding sentiment will be reversed to the corresponding bidirectional sentiment. A multi-polar emotional state change chain is established based on students' dominant emotions at different stages. The expression for judging students' emotional tendencies based on the emotional chain is shown in equation (7). This equation is used to determine students' emotional tendencies at a specific stage of learning. By analyzing the frequency of different types of emotions, it is possible to identify the dominant emotions in a specific learning stage, which is crucial for understanding students' emotional trends and predicting their learning behavior.

$$Sent_{tend}(L_i)=\max(Dmt_{pst,I}-freq) \quad (7)$$

In equation (7), $Sent_{tend}(L_i)$ represents the emotional inclination of the student. I is the frequency of dominant emotions in the current course progress. The setting of emotional tendency parameters is based on the analysis of the trend of students' emotional state changes.

Studying the frequency of dominant emotions at different stages to determine students' emotional tendencies can help predict changes in their behavior.

3.2 Construction of learning behavior prediction model based on SBPM

Based on FGSA, the results of student multi-polar emotional assessment can be used to analyze students' emotional trends. The emotion assessment model first identifies students' emotional states through FGSA techniques. This technology can identify and distinguish specific emotions of students in specific learning contexts, such as happiness, sadness, anger, etc. By constructing a multi-level emotion dictionary and quantifying the emotional intensity of sentences, the model can track students' emotional changes at different learning stages and identify patterns of rising, falling, or fluctuating emotions. A predictive model is constructed by combining students' emotional trends with learning behavior data, thereby enabling the prediction of their learning behavior based on their emotional state. If the student can graduate smoothly, there is no need to intervene in their learning behavior. If there are certain difficulties for students to graduate successfully, their learning behavior can be adjusted based on the results of emotional analysis. The algorithm logic is shown in Figure 4.

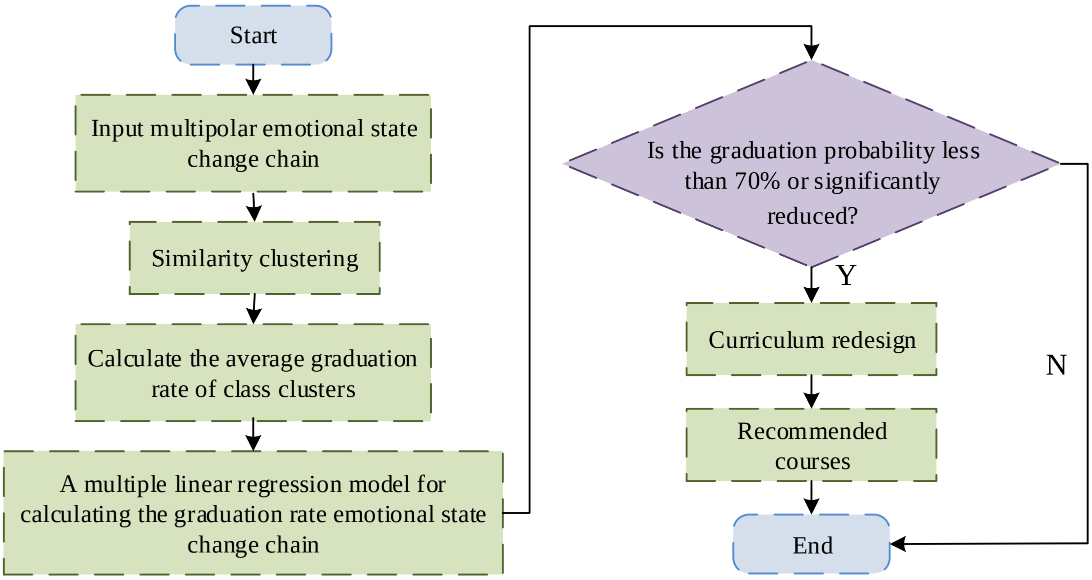


Figure 4: Algorithmic logic of the SBPM model

The construction of the SBPM model is intended to facilitate the analysis of SLB states by leveraging the emotional results of the student emotional assessment state model. This analysis is designed to assist educators in adapting their instructional content to align with students' emotional needs. When using the SBPM model to analyze the graduation rates of different students, it is necessary to perform similarity clustering on student emotions to calculate the average graduation probability of different students. When calculating the graduation probabilities of different students, it is needed to first normalize the student data to weaken the impact of extreme situations on the final calculation results. The normalization formula is shown in equation (8) [21, 22].

$$Dmt_{pst} - c(L_i) = \frac{Dmt_{pst}(v_1), \cdots, Dmt_{pst}(v_T)}{\max\left(Dmt_{pst}(v_t)\right) - \min\left(Dmt_{pst}(v_t)\right)} \tag{8}$$

In equation (8), $Dmt_{pst} - c(L_i)$ is the chain of changes in students' emotional states. $Dmt_{pst}(v_t)$ is the emotional intensity value. When determining whether a student can graduate, it is necessary to decompose their graduation status into levels based on the similarity of their multi-polar emotions. This study uses the cosine similarity method to calculate the cosine similarity between different students, as shown in equation (9) [23].

$$dist\left(Dmt_{pst}-c(L_i),Dmt_{pst}-c(L_j)\right)=\frac{\sum_{t=1}^{T}Dmt_{pst,i}(v_t)Dmt_{pst,j}(v_t)}{\sqrt{\sum_{t=1}^{T}Dmt_{pst,i}(v_t)^2}\sqrt{\sum_{t=1}^{T}Dmt_{pst,j}(v_t)^2}} \quad (9)$$

In equation (9), $dist\left(Dmt_{pst}-c(L_i),Dmt_{pst}-c(L_j)\right)$ is the similarity between student i and j. $Dmt_{pst,i}(v_t)$ is the normalized emotional intensity of i during class t. Student clustering analysis needs to be based on the similarity calculation results. During clustering analysis, the clustering radius is calculated using equation (10).

$$R=\Gamma(n)\frac{1}{\sqrt{\pi^n}}\frac{1}{n}\sqrt{\prod_{i=1}^{n}\prod_{j=1}^{n}dist\left(Dmt_{pst}-c(L_i),Dmt_{pst}-c(L_j)\right)} \quad (10)$$

In equation (10), R is the clustering radius. n is the size of the sample set. $\Gamma(n)$ is the gamma function. Finally, with the goal of increasing the probability of students graduating, a predictive model function can be constructed. The constructed prediction target multiple linear regression model is shown in equation (11).

$$Gp(L_i)=\beta_0+\sum_{t=1}^{T}\beta_t Dmt_{pst}-c(L_i)[t] \quad (11)$$

In equation (11), $Gp(L_i)$ is the student graduation probability output by the model. β is the partial regression coefficient. $Dmt_{pst}-c(L_i)[t]$ is the element value in the chain of students' multi-polar emotional state changes. When using this model to predict and analyze the graduation probability of students, the model loss needs to be considered, and the constructed loss function is shown in equation (12). This equation defines the loss function of the model, which measures the difference between the predicted and actual values of the model. The loss function is the main objective of optimization during the model training process. By minimizing the loss function, the model parameters can be adjusted to improve the accuracy of predictions.

$$Loss(\beta_0,\ldots,\beta_T)=\sum_{i=1}^{n}\left(Gp(L_i)-Gpat(L_i)\right)^2 \quad (12)$$

In equation (12), $Loss(\beta_0,\ldots,\beta_T)$ is the model loss. $Gpat(L_i)$ is the actual probability of students graduating. The research model is designed with universities as the target users, with a large number of students. Concurrently, students exhibit a spectrum of emotional fluctuations, rendering the data samples inherently multidimensional. This complexity precludes the application of conventional numerical computation techniques for model resolution. Mini-batch Gradient Descent (MBGD) uses a small batch of data samples per iteration to calculate the average gradient, rather than using the entire training set like Batch Gradient Descent (BGD) or only one sample like Stochastic Gradient Descent (SGD) [24, 25]. This method strikes a balance between computational efficiency and convergence speed, but it uses a fixed learning rate to solve the model, resulting in lower solving efficiency. Learning Rate Warm Restarts (LRWR) is a strategy for dynamically adjusting learning rates. It allows the learning rate to periodically increase and decrease during the training process, rather than simply decaying linearly or exponentially according to a predetermined decay strategy. Accordingly, this study proposes to enhance the MBGD with LRWR and refine the coefficients of the SLB prediction model through the implementation of the proposed algorithm, thereby optimizing the model's computational precision and efficiency. The improved MBGD algorithm flow is shown in Figure 5.

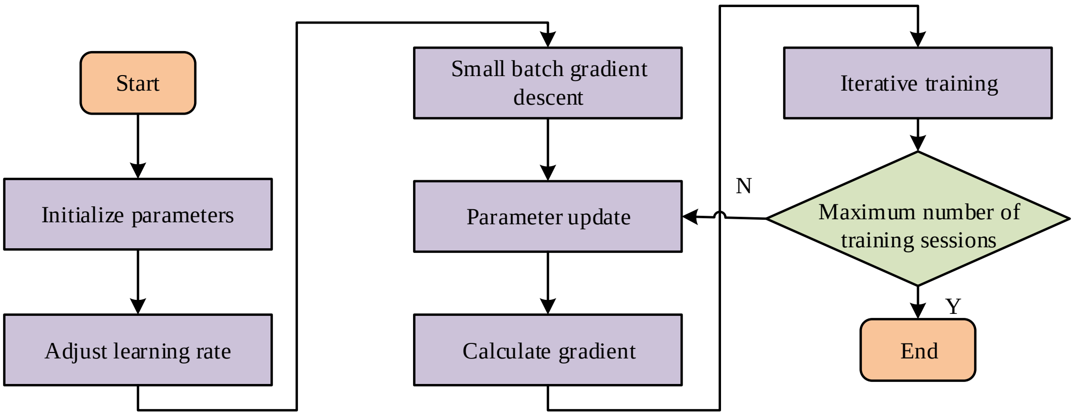


Figure 5: Model solving process for improving the MBGD algorithm based on LRWR

Improving the MBGD algorithm requires initializing the model parameters, adjusting the initial learning rate, and determining the batch size when solving the model. The data samples are divided based on batch size. Before each iteration of training starts, the order of the dataset is randomly shuffled, and small batches of data are sampled according to batch size to begin iterative training. During the training process, it is necessary to calculate the gradient and update the algorithm parameters based on the gradient. Finally, the above steps are repeated until the algorithm performance meets the requirements or reaches the maximum number of iterations. In this algorithm, when updating the learning rate, this study uses the sigmoid function to slow down the learning rate to reduce the problem of algorithm efficiency caused by a fixed rate decrease in the learning rate. When using the above method to update the partial regression coefficients of the model, the update function formula is shown in equation (13).

$$\beta_{t\_updt} = \beta_t + \frac{Lr_t}{b} \sum_{k=i}^{i+b-1} \left(Gp(L_k) - Gpat(L_k) \right) \times Dmt_{pst} - c(L_k)[t] \qquad (13)$$

In equation (13), β_{t_updt} is the updated value of the partial regression coefficient. b is the sampling interval for students. In the development of the SBPM model, the parameter adjustment steps include initializing the model parameters, setting an appropriate initial learning rate, and determining the batch size in MBGD. Subsequently, the dataset is divided into small batches of samples and the order of the dataset is randomly shuffled before each iteration to enhance the model's generalization ability. During the iterative training process, the gradient of each small batch of data is calculated and the model parameters are updated. At the same time, the learning rate and batch size are dynamically adjusted based on the performance evaluation results to optimize the model. Furthermore, a learning rate hot restart strategy is employed to facilitate periodic adjustments to the learning rate, thereby preventing the phenomenon of local minima. Additionally, a sigmoid function is utilized to decelerate the learning rate, thus enhancing the efficiency of the solution process. Finally, when the model loss drops to the preset threshold or reaches the maximum number of iterations, training is stopped to ensure that the model is both accurate and efficient.

4 Simulation analysis of SLB prediction model based on emotion analysis

4.1 Analysis of student emotional assessment model based on FGSA

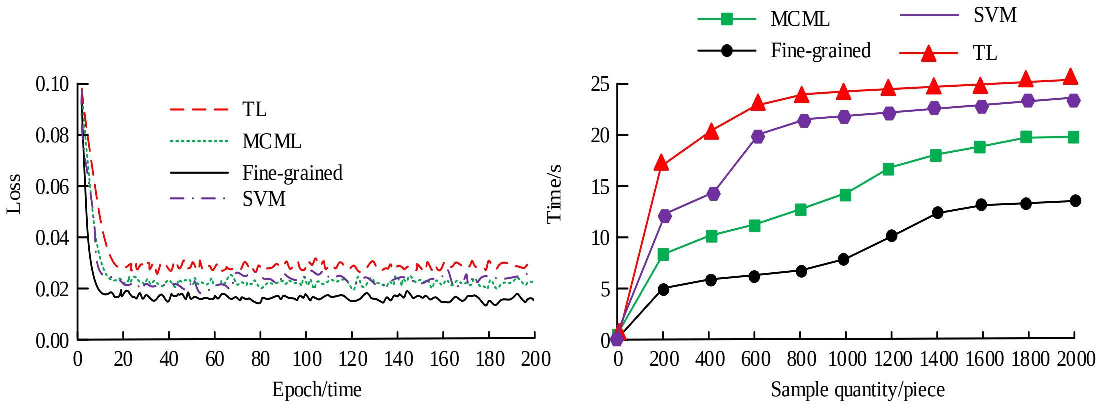
When conducting simulation analysis on the student emotional assessment model, this study randomly selects discussion texts from 2,500 students in a university during 12 hours of a certain course on an electronic learning platform as data samples. Among them, there are a total of 18,564 text data records. Table 3 shows the specific experimental configuration for training and simulation testing of the model.

Table 3: Experimental environment of student emotion assessment model simulation

Item	Type	Item	Type
Operating system	windows10	Programming Language	Java
Memory	2T	Programming type	Single threaded

			compilation
CPU	i7-7700k	Simulation platform	MATLAB
Equipped with RAM	16GB	Programming Library	Apache NetBeans

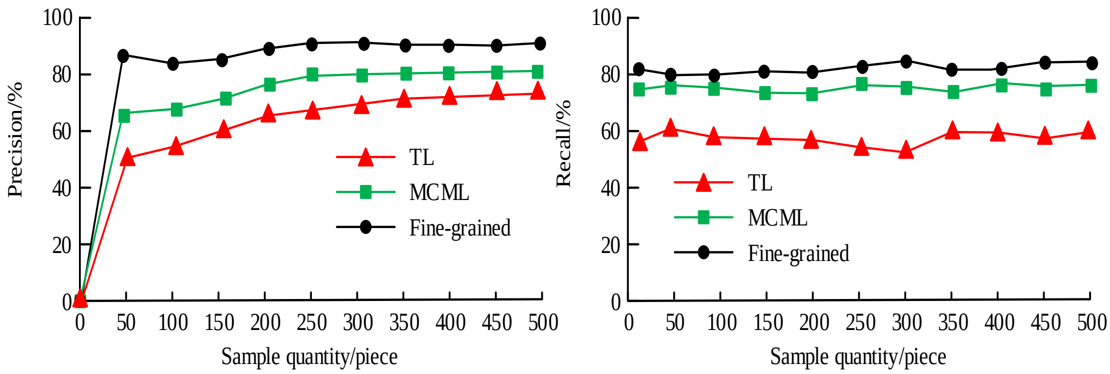
The research model (FGSA) is mainly used for sentiment classification. Pan W et al. proposed an emotion splitting model based on Multi-class Machine Learning (MCML) model. Cao Z et al. proposed an emotion classification method based on Transfer Learning (TL). To verify the effectiveness of the research model, the performance of three algorithms is compared. The changes in model loss value and evaluation efficiency are shown in Figure 6.



(a) Comparison results of model loss values (b) Comparison results of model efficiency

Figure 6: Model loss value of several computational efficiency comparison

Figure 6 (a) shows the changes in loss values for the three models. FGSA completes convergence in the 10th iteration and the loss value after model convergence can be reduced to below 0.02. Both MCML and TL converge at the 20th iteration, with MCML able to reduce the loss value to around 0.25, while TL maintains the loss value at around 0.03 after convergence. The convergence effect of the SVM benchmark model is also lower than that of the research model. FGSA has a faster convergence speed and a lower loss value after convergence. Figure 6 (b) shows the comparison results of emotion classification efficiency among three models. As the number of data samples increases, the time required for all three models to complete sentiment classification is also increasing. When the data volume increases to 2,000, FGSA takes about 12s to complete the sentiment classification task, MCML takes about 17s to complete the classification of all data, and TL takes more than 20s. Compared to MCML, the efficiency of FGSA has increased by nearly 30%. The SVM model also maintains a time consumption of around 20 seconds to complete the emotion classification task. Figure 7 compares the accuracy and recall of three models.



(a) Comparison results of model precision values (b) Comparison results of model recall values

Figure 7: Comparison of model precision and recall rate

Figure 7 (a) shows a comparison of the accuracy of three models. The accuracy of FGSA basically does not change with the number of data samples, and overall remains around 0.82. The accuracy of MCML and TL both increases with the increase of data sample size, with the highest accuracy of MCML being about 0.78 and the accuracy of TL being about 0.61. Figure 7 (b) shows the recall rates of the three models, which are largely unaffected by the number of data samples. The recall rate of FGSA remains at around 0.81, while MCML is slightly lower at around 0.78, and TL is much lower than these two models, with a recall rate of only around 0.60. Compared with other current emotion classification algorithms, the FGSA model always maintains a higher level of accuracy and recall when evaluating student emotions.

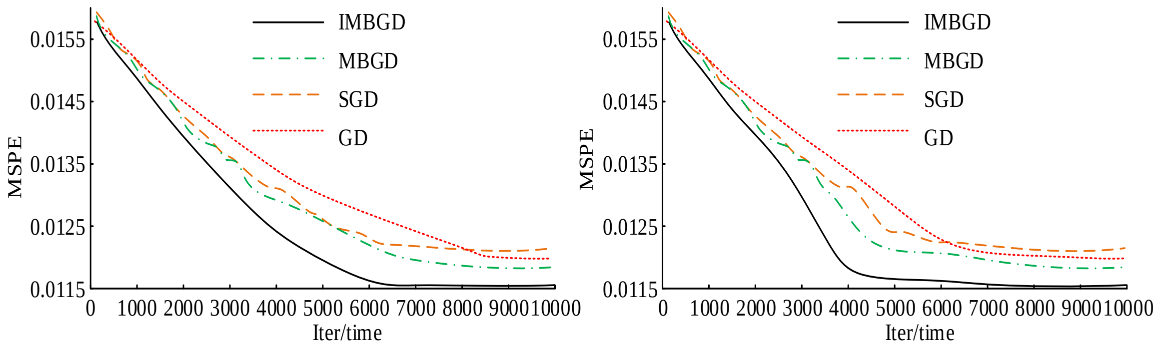
4.2 Construction of learning behavior prediction model based on SBPM

When conducting simulation analysis on the SBPM model, the experimental environment used is consistent with the student sentiment assessment model. The experimental data for this model also come from online learning platforms. To verify the applicability of the model in different environments, this study extracts data from online learning platforms of universities. In addition to the data from the simulation analysis of the student emotional assessment model, data from students of different grades in another university are also extracted. In this study, the first extracted data will be named Data 1, and the second extracted data will be named Data 2. Table 4 shows the parameter information of all algorithms, including the SBPM model.

Table 4: Algorithm parameter setting

Name	Value	Name	Value
Sampling interval	10	Duration of class hours	12
Convergence threshold	0.01	Data 1	2500
Iterations	10000	Data 2	2500

By modifying the sampling interval, the quantity of data utilized on each occasion that the model parameters are updated can be regulated. A smaller sampling interval can accelerate the model's adaptation speed to new data, but it may lead to increased fluctuations during the training process. A larger sampling interval can make the model update smoother and help the model converge stably. The implementation of an appropriate convergence threshold is an effective method for ensuring that the model terminates its training process at a predetermined level of accuracy. This approach helps to prevent the unnecessary expenditure of computational resources and the potential overfitting of the model to the training data. Setting an upper limit on the number of iterations can prevent overfitting of the model on the training data. By limiting the number of iterations, the complexity of the model can be controlled to some extent, enabling the model to have better generalization ability on unseen data. The choice of batch size directly affects the stability and convergence speed of model training. Through experiments and parameter tuning, a suitable batch size can be selected to enable the model to converge quickly and maintain good generalization performance during training. The algorithm used in the SBPM model is the MBGD algorithm, which is a common gradient descent algorithm. Therefore, when selecting the comparison algorithm, this study compares the performance of the original MBGD, SGD, and traditional Gradient Descent algorithm (GD). The Mean Square Percent Error (MSPE) results of different algorithms on two datasets are displayed in Figure 8.



(a) Data 1 (b) Data 2

Figure 8: Comparison results of MSPE values for different algorithms

Figures 8 (a) and (b) show the MSPE convergence of four algorithms on Data 1 and Data 2. In Figure 8 (a), as the iteration increases, the MSPE values of all algorithms decrease accordingly. After the MBGD algorithm converges, its MSPE value can be reduced to around 0.0115. The MSPE values of the remaining algorithms after convergence are around 0.012. In Figure 8 (b), on the Data 2 dataset, the convergence speed of all algorithms will accelerate, and the MSPE value of the converged algorithm will also decrease to a certain extent. Figure 9 shows the efficiency comparison of four algorithms on two datasets.

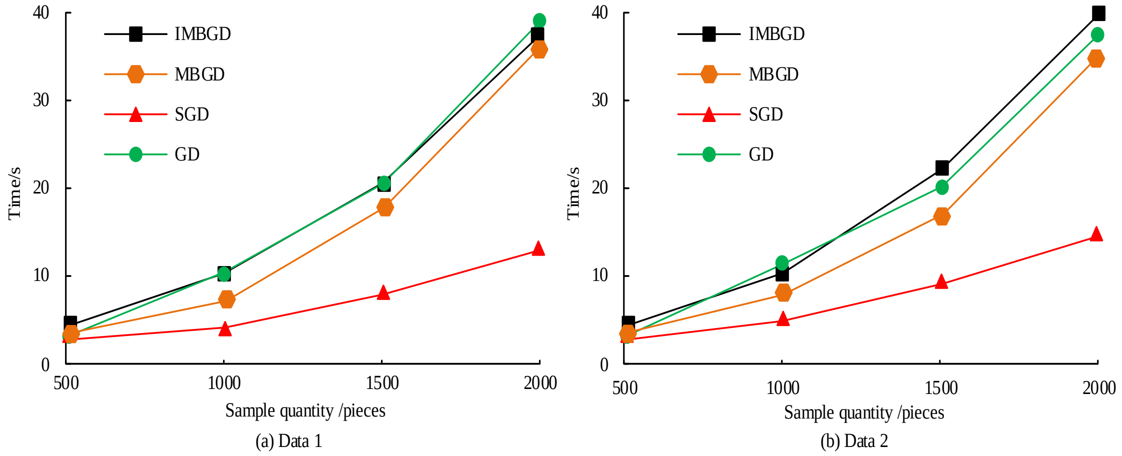


Figure 9: Time-cost comparison results for the different algorithms

Table 5: Comparing the results of the F1 to and accuracy of the four algorithms

Model	Date 1		Date 2	
	F1	Accuracy (%)	F1	Accuracy (%)
IMBGD	0.964	97.4	0.959	98.4
MBGD	0.918	92.3	0.906	91.1
SGD	0.906	91.1	0.911	92.1
GD	0.867	89.7	0.877	90.7

Figure 9 (a) shows the time cost of the algorithm on Data 1 and Data 2. In Figure 9 (a), SGD takes the shortest time to complete LBA tasks, while the time difference between other algorithms is relatively small. SGD only takes about 10 seconds to complete LBA for 2,000 samples, while other algorithms take around 35 seconds. In Figure 9 (b), SGD has the shortest time consumption, the rest of the time costs have increased to a certain extent, while MBGD has the most significant increase in time cost. The study further compares the F1 values and accuracy of four models, and the results are shown in Table 5. By comparing the F1 scores and accuracy of different models on different datasets, the generalizability of the research model in the field of education can be further validated.

As shown in Table 5, the IMBGD algorithm achieves an F1 value of 0.95 or above, while maintaining an accuracy of over 97% in both datasets. The F1 values of the other three algorithms remain around 0.90, while the accuracy remains around 90%. The performance of the IMBGD algorithm is significantly better than the other three algorithms. In Data 1 and Data 2, this study randomly selects 10 students who are predicted to be unable to graduate, analyzes their graduation probabilities, and compares their graduation probabilities after receiving recommended learning behaviors, as shown in Figure 10.

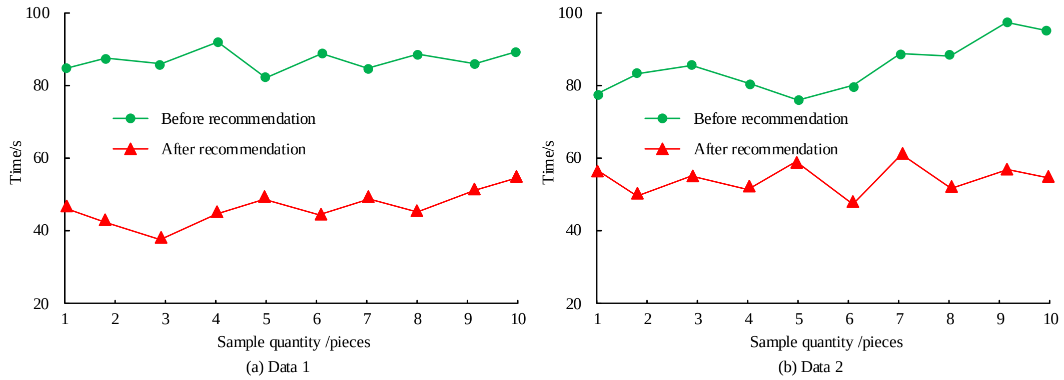


Figure 10: Comparison of student graduation probability change

Figures 10 (a) and (b) show the changes in graduation rates of 10 students in two datasets after receiving learning behavior recommendations. In Figure 10 (a), the graduation rate of students remains around 50% before accepting the school's recommendations for changing their learning behavior. After accepting the school's advice and correcting their own learning behavior, the graduation rate of all students has reached over 80%, and even some students have a graduation rate of 90%. In Figure 10 (b), the graduation rate is similar to the changes in students in Data 1, and the changes are more pronounced. Taking X High School as an example, the study selects 10 different classes and uses the designed model to predict the learning behavior of students in these classes. Based on the predicted learning behavior results, the students' learning courses are adjusted. The results are shown in Table 6.

Table 6: Practical application effect of the design model in X High school

Class ID	Class graduation rate (%)	Class ID	Class graduation rate (%)
1	98	6	100
2	100	7	100
3	99	8	98
4	98	9	100
5	100	10	99

As shown in Table 6, after applying the research model to this experimental class, the graduation rate of all classes can reach 98% or above. This suggests that the research model can also be effectively applied in practical settings to predict SLB, allowing for the adaptation and optimization of course content based on current learning behaviors, with the aim of enhancing students' learning outcomes.

5 Discussion

The study has achieved significant results in the field of SLB analysis by combining FGSA and SBPM. The FGSA model provides key inputs for the SBPM model by accurately identifying and quantifying students' emotional changes during the learning process. Compared with existing methods, the research model achieved an accuracy of over 80% in emotion recognition, largely due to the construction of a multi-level emotion dictionary and the application of synonym matching and weighting methods. Compared with the SOTA solution mentioned in related work, the research model performed well in both accuracy and recall of sentiment analysis. For example, compared with MCML and TL models, the research model has improved efficiency by nearly 30% in sentiment classification tasks and has lower loss values. The observed performance differences stem from multiple factors. Firstly, the research model emphasizes the granularity of emotion analysis during the construction process, which enables the model to more accurately capture subtle changes in students' emotions. Secondly, advanced optimization strategies are adopted in the model training, which help the model to break out of local minima and find better solutions during the training process. The model fully considers individual differences among students during design and improves its applicability and accuracy through personalized emotional assessment and behavior prediction. In education, accurate prediction of learning behavior can help teachers and educational administrators better understand students' learning needs, thereby designing more effective teaching strategies and intervention measures. In addition, the potential of this model in improving student learning efficiency and graduation rates provides universities with a new tool to optimize educational resource allocation and curriculum design. In the long run, this emotion-based learning behavior prediction method is expected to play a greater role in personalized education and lifelong learning.

6 Conclusion

To improve the level of higher education and enhance students' study habits, this study constructed a student emotional assessment model based on FGSA technology. This model could analyze the emotional trends of students during the learning process. Based on the trend of student emotional changes output by the emotional assessment model, this study constructed an SLB predictive analysis model. The model used cluster analysis to preprocess the sample data and constructed an objective function based on the linear regression equation. When solving the objective function, an improved MBGD algorithm was used. The results showed that the research model achieved an accuracy of over 80% in analyzing students' emotions, while also stabilizing the algorithm's recall rate at around 80%. The emotional evaluation model could reduce the loss value to below 0.02 when analyzing students' emotions while keeping the calculation time within 15 seconds. The student LBA prediction model could reduce the loss value to around 0.0115 when predicting and analyzing SLB, but the time consumption was relatively high, requiring more than 35s. After providing special tutoring to students based on SLB prediction analysis results, the graduation rate of students could significantly increase. Universities could provide additional tutoring and correction to students based on the predicted results of SLB, effectively improving the teaching level of universities. However, the designed SLB prediction model has a high computational time when analyzing predictive learning behavior. In the future, the model-solving method will be further optimized to reduce the time cost of model-solving.

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