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PAPER

Exploring Blended Learning Models Supported by Mobile Interactive Technologies in Higher Education

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ABSTRACT

With the widespread adoption of mobile interactive technologies and the evolving landscape of higher education, blended learning models have increasingly become a focus of educational reform. These models integrate traditional face-to-face teaching with modern online learning approaches, enhancing learning flexibility and interactivity through mobile technologies. Although blended learning has shown significant advantages in enhancing teaching efficiency and meeting individual student needs, research on its impact on student emotional interaction remains relatively limited. Emotional factors play a crucial role in the learning process, affecting student motivation and outcomes. Current research on emotional interactions in blended learning primarily relies on traditional methods, such as surveys, which frequently do not offer real-time and precise emotional data. Therefore, this paper aims to explore the effective selection of emotional sensing nodes and the accurate extraction of emotional features through mobile interactive technology-supported blended learning. The findings of this study aim to enhance the quality of teaching interactions but also to provide theoretical and practical support for optimizing blended learning models.

KEYWORDS

blended learning, mobile interactive technology, emotional analysis, teaching interaction, higher education

1 INTRODUCTION

In the context of rapid globalization and information technology, higher education is facing significant transformations. Mobile interactive technologies, such as smartphones and tablets, have become indispensable in students' daily lives, offering new opportunities and environments for education [1–4]. Blended learning models, which combine traditional face-to-face teaching with online learning, are increasingly becoming an important component of higher education [5, 6]. By leveraging the advantages of mobile interactive technologies, these models greatly enhance teaching flexibility and interactivity, meeting the diverse learning needs of students [7].

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However, despite the widespread acclaim for blended learning models, their practical application in teaching and their impact on learning emotions still require in-depth research [8–10]. Emotional factors play a crucial role in the learning process and can significantly affect students' motivation, engagement, and effectiveness [11]. Therefore, exploring emotional interactions in blended learning supported by mobile interactive technologies is crucial for optimizing teaching strategies and improving teaching quality.

Current research primarily focuses on assessing the effects of blended learning and the application of technologies, with insufficient discussion on the analysis and application of emotional interactions in teaching. Existing studies often use questionnaires or simple observation methods to assess emotional states, which often lack real-time accuracy [12–15]. Moreover, the specific implementation and optimization of emotional analysis in blended learning models have not yet developed a mature theoretical and methodological framework, limiting the in-depth development and widespread application of blended learning models in higher education [16–18].

This paper aims to address this research gap and is divided into two main parts for a thorough exploration. First, the research will focus on analyzing emotional interactions in blended learning supported by mobile interactive technologies. This includes selecting emotional sensing nodes and extracting emotional characteristics from blended learning interactions. Second, based on the aforementioned emotional analysis, a highly adaptive and interactive blended learning model will be constructed. Through this research, not only can the quality of teaching interactions be enhanced, but scientific methodological support can also be provided for measuring and applying learning emotions. This, in turn, promotes innovation in higher education teaching models and enhances the personalization and effectiveness of education.

2 ANALYSIS OF EMOTIONAL INTERACTION IN BLENDED LEARNING SUPPORTED BY MOBILE INTERACTIVE TECHNOLOGIES

In the field of higher education, the introduction of mobile interactive technologies has provided blended learning environments with unprecedented dynamism and interactivity. These technologies enable students to access learning resources anytime and anywhere, while also allowing real-time communication with teachers and peers. However, the analysis of emotional interactions under this new teaching model has not been sufficiently explored. Emotional factors directly affect students' learning motivation and information absorption efficiency, which has a profound impact on teaching effectiveness. Therefore, conducting an analysis of emotional interactions in blended learning supported by mobile interactive technologies holds significant research value. Especially in selecting emotional sensing nodes, it is crucial to accurately filter out key textual data that reflects students' emotional states, such as forum discussions and online feedback. Figure 1 illustrates the mobile interactive technology service model focused on emotional interaction analysis in blended learning.

Moreover, in blended learning, the effective extraction of emotional textual features and sentiment analysis can reveal students' emotional reactions and tendencies in specific teaching environments. This provides data support for teachers to enhance teaching strategies. By analyzing the textual data generated by students on mobile interactive platforms, it is possible to identify the intensity, polarity, and trends of emotions. This information is crucial for constructing a supportive and adaptable blended learning model and teaching environment. A blended learning model based on sentiment analysis can better meet students' emotional and cognitive needs, enhancing their motivation and perseverance in learning. Figure 2 depicts the abstract model of emotional interaction analysis in blended learning.

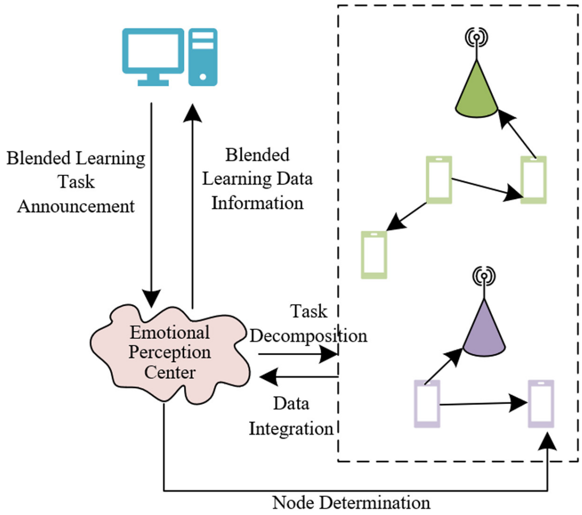

Fig. 1. Mobile interactive technology service model for emotional interaction analysis in blended learning

2.1 Selection of emotional sensing nodes in blended learning

This study explores the selection of emotional textual data and sensing nodes in blended learning supported by mobile interactive technologies. Unlike traditional sensing node selection based primarily on time, geographic location, and user behavior data, this study focuses on selecting teaching interactive textual data containing rich emotional vocabulary. By constructing a sensing network model and using genetic algorithms to classify the teaching textual data carried by nodes, this study selects the textual data nodes that can most effectively reflect students' emotional states for iterative optimization based on the node's fitness function. This method is particularly suitable for blended learning environments in higher education. It optimizes the selection process of sensing nodes, improves data processing efficiency, and enhances the accuracy of emotional analysis by reducing unnecessary data acquisition and screening.

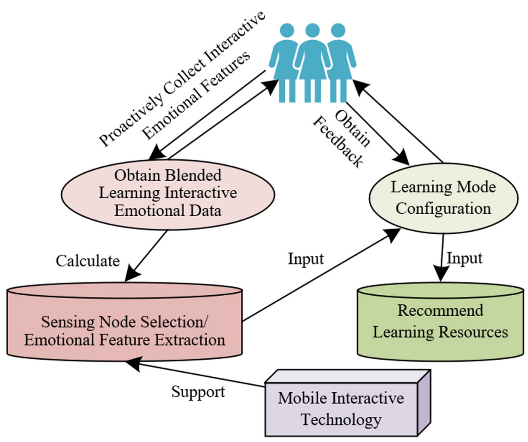

Fig. 2. Abstract model of emotional interaction analysis in blended learning

For the blended learning environment supported by mobile interactive technologies, this paper utilizes genetic algorithms to optimize the selection process of emotional textual data and sensing nodes. Unlike the selection of nodes in traditional crowd-sensing environments, the focus here is on emotional textual data in teaching interactions, which is crucial for understanding and improving students' emotional responses. First, the nodes involved in the sensing service are binary encoded, enabling us to process a vast amount of node data efficiently and optimize node selection iteratively by simulating natural selection.

Assume there is a set of service nodes containing l nodes, denoted by $o = \{o_1, o_2, ..., o_l\}$, where each node carries l pieces of data information, i.e., $o_u = \{h_1, h_2, ..., h_l\}$. If the node o_u is selected, the corresponding data information h_u is marked as *1*; if the node o_u is not selected, it is marked as 0.

$$h_u = \begin{cases} 1, o_u \ \textit{is selected} \\ 0, o_u \ \textit{is not selected} \end{cases} \tag{1}$$

When using genetic algorithms to select nodes that support emotional perception in blended learning interactions, the fitness function is crucial. The design of the fitness function is as follows:

Firstly, the initial consideration of the fitness function is the combined probability of carrying textual data, denoted as *S*. In blended learning, textual data typically contains a wealth of teaching interaction information, which is crucial for analyzing students' learning behavior and emotional states. The setting of the *S* value reflects the probability that at least one node in the selected service set carries textual data. A higher *S* value indicates a greater richness of textual data in the node set, which is more likely to contain crucial emotional and teaching interaction information, serving as a significant source for emotional analysis. Assuming that the probability that the selected node *u* carries textual information is represented by $s_u = l_u/v_u$, where l_u is the amount of textual data carried by node *u* and v_u is the total amount of information carried by node *u*, the calculation formula is as follows:

$$S = 1 - \prod_{o_u \in o'} (1 - s_u) \tag{2}$$

Secondly, the combined probability of containing emotional words, denoted as *T* and serving, as the second dimension of the fitness function, emphasizes the likelihood that the textual information of the selected nodes includes emotional words. In blended learning, the presence of emotional words directly relates to the expression of student emotions, which is a key indicator for understanding student engagement and satisfaction. Therefore, the size of the *T* value directly impacts the node's value in emotional analysis. A higher *T* value indicates that the node is more likely to assist in analyzing students' emotional states. Assuming the probability that the selected node *c*'s textual information contains emotional words is ${}_it_u$, the probability that node *u* carries information that is both textual and contains emotional words is represented by *o*(*ts*), and the probability that node *u* carries textual data is represented by *o*(*s*). The calculation formulas are:

$$T = 1 - \prod_{o_u \in o'} (1 - t_u) \tag{3}$$

$$t_u = o\left(t \middle| s\right) = \frac{o(ts)}{o(s)} \tag{4}$$

Third, the combined number of emotional words, *Z*, measures the average number of emotional words in the selected nodes. When dealing with complex teaching interaction data, a single node may not offer a comprehensive overview of emotions. Therefore, it is essential to evaluate the intensity of emotional expression across the entire node set by averaging the number of emotional words. A higher Z value indicates that the node set contains more emotional words, which can effectively reveal students' emotional tendencies and responses. This is crucial for formulating or adjusting teaching strategies. Assuming that the number of emotional words contained in the textual information carried by the selected node u is represented by z_u, then the calculation formula is:

$$Z = \frac{\sum_{o_u \in o'} t_u \times z_u}{v} \tag{5}$$

Lastly, the comprehensive consideration of the three core parameters S, T, and Z forms the main body of the fitness function, which is particularly important in a blended learning environment supported by mobile interactive technologies. This setup ensures that the fitness function reflects not only the type of data carried by the nodes and their emotional richness but also the comprehensive emotional value of the node data. By using a fitness function, it is possible to effectively select nodes that are most valuable for emotional analysis in blended learning, thereby enhancing teaching quality and improving learning outcomes. The fitness function is set as follows:

$$d(s,t,z) = Z = \frac{\sum_{o_u \in o'} t_u \times z_u}{v} \tag{6}$$

2.2 Emotional feature extraction in blended learning interactions

In the blended learning environment of higher education, the widespread use of mobile interactive technologies highlights the importance of emotional feature extraction in optimizing the learning experience and improving teaching interaction efficiency. Traditional feature selection methods, such as chi-square statistics and information gain, have certain limitations when dealing with emotional text data in educational interactions. Chi-square statistics may overlook the true frequency impact of a feature word in classification, while information gain may not accurately reflect the importance of a feature word to a specific category. This is particularly evident in blended learning, where the teaching environment relies on precise emotion recognition to adjust teaching strategies and enhance the personalized experience of student interaction. Therefore, this study proposes an enhanced feature selection algorithm that combines information gain and *CHI*. It introduces a weight β to address the limitations of both methods, thereby improving the distinctiveness and accuracy of emotional features in blended learning supported by mobile interactions. This enhanced method not only adjusts to the intricate and fluctuating teaching scenarios in higher education but also improves the efficiency of feature extraction and the relevance of teaching content.

Assuming category z and texts containing feature, word s are represented by X, texts not in category z but containing feature word s by Y, texts in category z but not containing feature word s by Z, and texts neither in category z nor containing feature word s by F, the total number of texts is represented by V. The following formula gives the *CHI* statistic expression for feature variable s with respect to category z under the assumption of independence:

$$\phi^2(s,z) = \frac{V(XF - YZ)^2}{(X+Y)(X+Z)(Y+F)(F+Z)} \tag{7}$$

In the information gain method, category Z is a variable represented by $Z_1, Z_2, \ldots, Z_v$. Assuming the total number of categories is represented by v, the probability corresponding to the occurrence of category Z is represented by $O(Z_1), O(Z_2), \ldots, O(Z_v)$. The following formula provides the calculation for the entropy of the classifier:

$$G(Z) = -\sum_{u=1}^{v} O(Z_u)\log_2 O(Z_u) \tag{8}$$

Assuming the probability of event S occurring is represented by $O(s)$, and the probability of S not occurring is represented by $O(\bar{s})$. The formula for calculating the entropy without feature s is as follows:

$$G\left(Z\middle|s\right) = O(s)G\left(Z\middle|s\right) + O(\bar{s})G\left(Z\middle|\bar{s}\right) \tag{9}$$

The information gain provided to the classifier by feature S is calculated as follows:

$$\begin{aligned} UH(S) = -\sum_{u=1}^{v} O(Z_u)\log_2 O(Z_u) + O(s)\sum_{u=1}^{v} O\left(Z_u\middle|s\right)\log_2 O\left(Z_u\middle|s\right) \\ +O(\bar{s})\sum_{u=1}^{v} O\left(Z_u\middle|\bar{s}\right)\log_2 O\left(Z_u\middle|\bar{s}\right) \end{aligned} \tag{10}$$

The expression for the enhanced algorithm proposed in this paper is:

$$ZKU\_UH(S,Z) = \beta UH(S) + (1-\beta)\phi^2(s,z) \tag{11}$$

To ensure the accuracy of emotional analysis and the relevance of teaching content, this paper further multiplies the ZGU_UH (S, Z) value of emotional feature words by an α value. This is represented as:

$$ZKU\_UH(S,Z) = (\alpha b + 1) \times [\beta UH(S) + (1-\beta)\phi^2(s,z)] \tag{12}$$

Experimental data analysis indicates that when the β value is 0.48, the algorithm achieves its peak accuracy. Beyond this value, the insufficiency of information gain starts to impact classification accuracy, resulting in a decline in performance. Moreover, the α value is specifically used to enhance the distinction of emotional feature words, thereby further improving the precision of emotional analysis. In experiments, when the α value is set to 0.248, the maximum improvement in classification accuracy is observed. Therefore, the final calculation formula for the feature selection algorithm is determined as follows:

$$\begin{aligned} & ZGU\_UH(S,Z) = (0.248b + 1) \times [0.48UH(S) + 0.52\phi^2(s,z)] \\ & \text{where, } b = \begin{cases} 0, \textit{Selected feature words are non}-\textit{emotional words} \\ 1, \textit{Selected feature words are emotional words} \end{cases} \end{aligned} \tag{13}$$

This strategy is particularly suitable for blended learning environments because it can more accurately manage the complex emotional data generated by student interactions. Compared to emotional feature extraction methods in other crowd-sensing environments, this method better captures the dynamic interactions and emotional changes between individuals. Such an approach not only enhances the personalized adaptability of the teaching content but also promotes real-time adjustment of teaching strategies to meet the specific learning and emotional needs of students.

3 CONSTRUCTION OF BLENDED LEARNING MODELS BASED ON EMOTIONAL ANALYSIS

After completing the analysis of emotional interactions in blended learning supported by mobile interactive technologies, this paper further designs four teaching and learning strategies for a new blended learning model based on the analysis results. These include assessment feedback strategies based on classroom response systems (CRS), self-paced learning strategies based on micro-videos, collaborative learning strategies based on heterogeneous grouping, and peer evaluation strategies based on self-reflection. Figure 3 illustrates the design framework for the blended learning model grounded in emotional analysis.

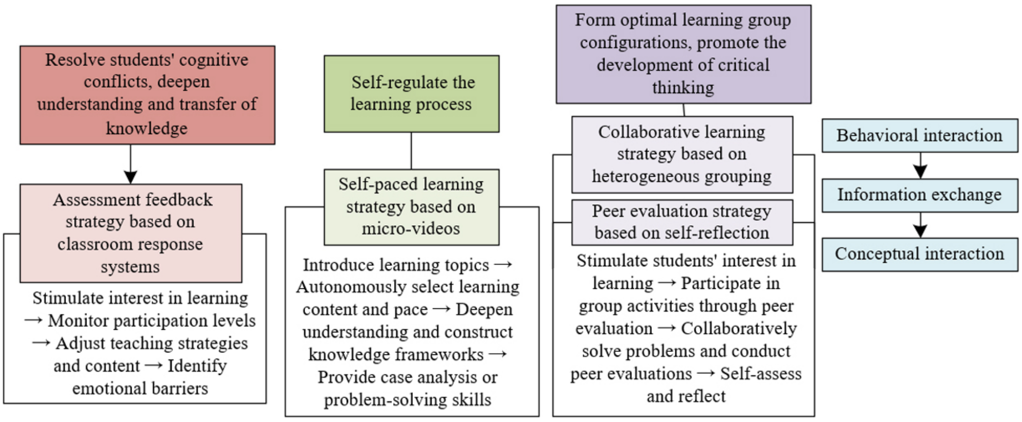

Fig. 3. Design framework for blended learning model based on emotional analysis

In the blended learning environment of higher education, the assessment feedback strategy based on CRS plays a key role by integrating the application of mobile interactive technologies. Considering the results of emotional analysis, this study has designed a strategy to capture and analyze students' emotional reactions during the learning process using mobile interactive technologies to enhance the assessment feedback of CRS. This strategy utilizes real-time emotional data to adjust teaching content and methods based on system feedback. This goal is to resolve students' cognitive conflicts, deepen their understanding, and enhance the transfer of knowledge. The CRS not only offers real-time learning feedback but also adapts the difficulty of questions and learning pace according to changes in students' emotional states, fostering the advancement of higher-order thinking skills. In the blended learning model, emotional recognition is achieved through mobile devices during the situational simulation phase to stimulate students' interest and motivation. During the participation phase, emotional data is utilized to monitor student engagement and adapt teaching activities to improve interactivity. During the knowledge construction phase, teaching strategies and content are adjusted by analyzing emotional responses to promote deep understanding and internalization of knowledge. During the problem-solving phase, emotional analysis assists teachers in identifying emotional obstacles that students may encounter in the process, enabling them to offer timely support. Finally, in the evaluation and reflection phase, the CRS combines emotional feedback to assist students and teachers in reflecting and evaluating, thereby promoting continuous improvement of learning outcomes. This teaching model integrates technology and emotional analysis to enhance students' learning experiences as well as improve the personalization and efficiency of teaching.

In higher education's blended learning environment, the application of mobile interactive technology can significantly enhance teaching and learning experiences.

Through self-paced learning strategies based on micro-videos combined with emotional analysis, students' engagement and autonomy can be effectively enhanced. This strategy allows students to regulate their learning process based on their own pace and emotional state using micro-videos. In practice, students watch micro-videos on their mobile devices while the system monitors their emotional reactions using emotional analysis technology to identify emotional triggers in the learning materials. Teachers can adjust video content and teaching pace based on analysis results, ensuring that each student learns at the most suitable speed and in the right context. This strategy not only enables students to engage deeply in the learning process but also adjusts teaching content in real-time to address students' emotional needs, thereby enhancing the personalization and effectiveness of teaching. The necessary technological support includes classroom management systems, screen recording software, and video editing software, which are essential tools for implementing self-paced learning. In the blended learning model, teachers start by creating engaging micro-videos using emotional analysis technology during the situational stimulation phase. This allows them to monitor students' reactions and adjust video content to effectively introduce learning topics. During the participation phase, students autonomously select learning content and pace using mobile devices based on their emotional states and learning preferences, which enhances their activeness and engagement in learning. During the knowledge construction phase, teachers adjust their teaching strategies based on emotional feedback analysis, which helps students deepen their understanding and construct knowledge frameworks. During the problem-solving phase, microvideos offer case analyses or problem-solving tips. They enable students to give real-time feedback on challenges and emotional experiences, facilitating the creation of personalized solutions. Finally, in the evaluation and reflection phase, emotional analysis is used to assess students' emotional reactions to the learning content. This process involves reflecting on and optimizing micro-video content to ensure continuous improvement in teaching effectiveness. This teaching model dynamically adjusts content and methods not only in response to students' immediate emotional needs but also promotes deep learning.

In a blended learning environment supported by mobile interactive technologies, collaborative learning strategies based on heterogeneous grouping enhance students' collaborative learning efficiency and motivation by integrating findings from emotional analysis. This strategy utilizes scientifically effective clustering algorithms that combine students' emotional tendencies, learning styles, and knowledge levels for grouping. This ensures diversity and balance in each group, thereby enhancing internal communication and cooperation. In practice, mobile interactive technologies such as spreadsheets and data analysis software are utilized to collect and process student information for creating optimal learning group configurations. Through this method, teachers can monitor the emotional dynamics of group interactions in real-time. By adjusting teaching strategies and group tasks accordingly, they can effectively stimulate students' collaborative thinking and enhance team collaboration effectiveness. In the blended learning model, teachers initially use emotional analysis results to design engaging learning activities during the situational stimulation phase, aiming to stimulate students' interest in learning. During the participation phase, the heterogeneous grouping strategy enables students to engage in group activities according to their emotional states and learning needs, thereby boosting interactivity and engagement in the learning process. During the knowledge construction phase, group members utilize their strengths to collaboratively solve problems, fostering a profound understanding and transfer of knowledge. During the problem-solving phase, groups encounter challenges collectively, utilizing emotional analysis feedback to adapt resolution strategies, thereby ensuring active participation from all members. Finally, in the evaluation and reflection phase, mobile interactive technologies are used to collect and analyze the emotional and cognitive performances of groups, assisting teachers and students in conducting effective reflection to optimize future learning strategies and group dynamics.

During the evaluation and reflection phase of blended learning, peer evaluation strategies that incorporate self-reflection utilize mobile interactive technologies and emotional analysis to enhance students' reflective thinking and metacognitive abilities. Through online evaluation platforms and digital whiteboards, students can assess their peers' assignments and performances while also receiving feedback from their peers. During this process, emotional analysis tools help identify students' emotional states during the evaluation process, such as satisfaction, frustration, or encouragement. This emotional data provides feedback for teachers, helping them understand students' reflective processes and emotional changes. This, in turn, allows teachers to adjust teaching methods and evaluation strategies to ensure that evaluation activities not only promote academic achievement but also strengthen students' emotional and psychological development. Ultimately, this leads to a more comprehensive educational effect. In the blended learning model, specifically during the situational stimulation phase, students are guided to contemplate the content they will learn through pre-set reflective tasks, which helps to ignite their enthusiasm for learning. During the participation phase, students actively participate in the teaching process through peer evaluation activities. Real-time emotional feedback assists them in adjusting their learning attitudes and methods. During the knowledge construction phase, peer evaluation encourages students to think deeply and understand the teaching content, enhancing the internalization of knowledge. During the problem-solving phase, students enhance their understanding of problems by evaluating their peers' solutions, thereby improving their problem-solving abilities. During the evaluation and reflection phase, peer evaluation becomes a crucial tool for students to self-assess and reflect. It not only helps them recognize their learning effectiveness but also fosters the development of metacognitive skills. This strategy, through continuous peer feedback and self-reflection, greatly enhances the depth and breadth of the learning process.

4 EXPERIMENTAL RESULTS AND ANALYSIS

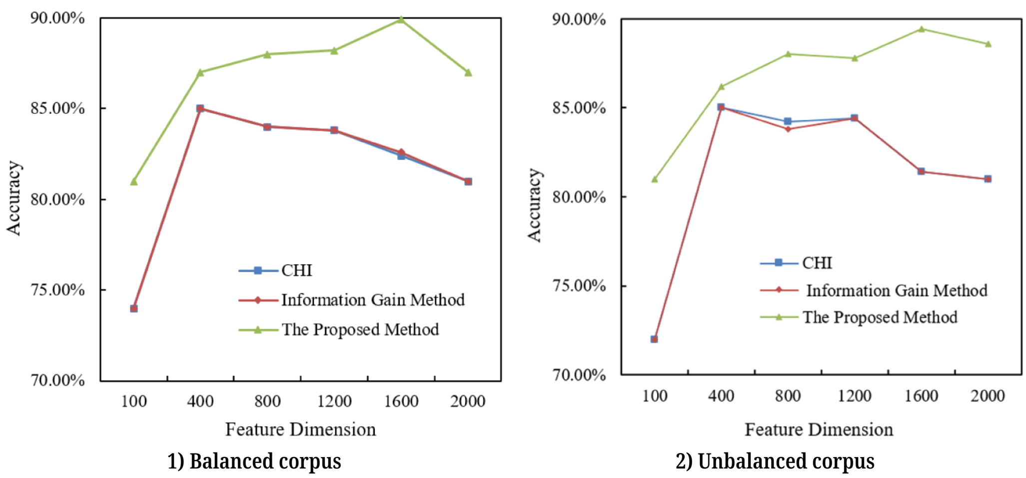

Fig. 4. Classifier accuracy in the improved feature selection algorithm across different dimensions

From Figure 4, it can be seen that in both balanced and unbalanced corpus environments, the enhanced feature selection algorithm proposed in this paper has consistently shown an advantage across various feature dimensions. For the balanced corpus, as the feature dimension increases from 100 to 1600, the classifier accuracy of our method grows from 81.00% to 89.90%, but slightly drops to 87.00% at a feature dimension of 2000. Similarly, in the unbalanced corpus, our method's accuracy increases from 81.00% to 89.40% (with a feature dimension of 1600), then slightly decreases to 88.60% (with a feature dimension of 2000). Compared to traditional *CHI* and information gain methods, our approach demonstrates higher accuracy across most feature dimensions, showcasing the algorithm's effectiveness and stability. These results suggest that the feature selection algorithm proposed in this paper effectively enhances classifier accuracy, especially at higher feature dimensions. This demonstrates that the enhanced algorithm can more effectively adjust to various data set balances and holds significant practical value for analyzing emotional interactions in blended learning.

Table 1. Statistical results of teacher-student interaction behaviors during blended learning processes

Code	Teacher-Student Behavior	Experimental Group Frequency	Experimental Group Percentage	Subtotal	Control Group Frequency	Control Group Percentage	Subtotal
1	Teacher Feedback	25	1.48%	11.25%	8	0.48%	26.35%
2	Teacher Questioning	42	2.36%		21	1.21%	
3	Teacher Lecturing	234	12.38%		435	23.68%	
4	Teacher Directives	23	1.38%		12	0.64%	
5	Student Response	127	7.45%	57.46%	82	4.68%	48.57%
6	Student Questioning	35	2.36%		0	0.00%	
7	Student Collaboration	635	37.45%		348	21.58%	
8	Independent Study	178	11.23%		412	22.68%	
9	Chaos	0	0.00%	21.36%	7	0.42%	22.36%
10	Silence	378	21.58%		389	22.69%	

Table 1 presents the frequency and percentage statistics of teacher-student interaction behaviors in the experimental and control groups during the blended learning process, illustrating the impact of integrating mobile interactive technology into the teaching process. The data show that the experimental group exhibited higher activity levels in most interaction types compared to the control group, particularly in "student collaboration" (37.45% vs. 21.58%) and "independent study" (11.23% vs. 22.68%). However, the independent study behavior was lower than that of the control group, indicating a shift towards more interactive behavior categories. Additionally, the proportion of "teacher lecturing" in the experimental group (12.38%) is significantly lower than that in the control group (23.68%). This suggests that the use of mobile interactive technology encourages more two-way interaction than one-way teaching. These statistical results clearly demonstrate that the blended learning model, based on mobile interactive technology, effectively enhances teacher-student interaction. It particularly fosters the development of students' collaboration and independent learning skills. The experimental group's performance in "student questioning" and "student collaboration" was particularly notable. While no "student questioning" was observed in the control group, 2.36% of students in the experimental group exhibited this behavior. This suggests that students are more willing and able to express their questions and thoughts in an environment supported by mobile interactive technology. Additionally, the high frequency of student collaboration reflects the learner-centered and cooperative learning emphasized in this teaching model. Through this model, not only is dynamic participation in learning enhanced, but the emotional quality of the learning process is also optimized, reflecting the effectiveness of the blended learning model construction based on emotional analysis.

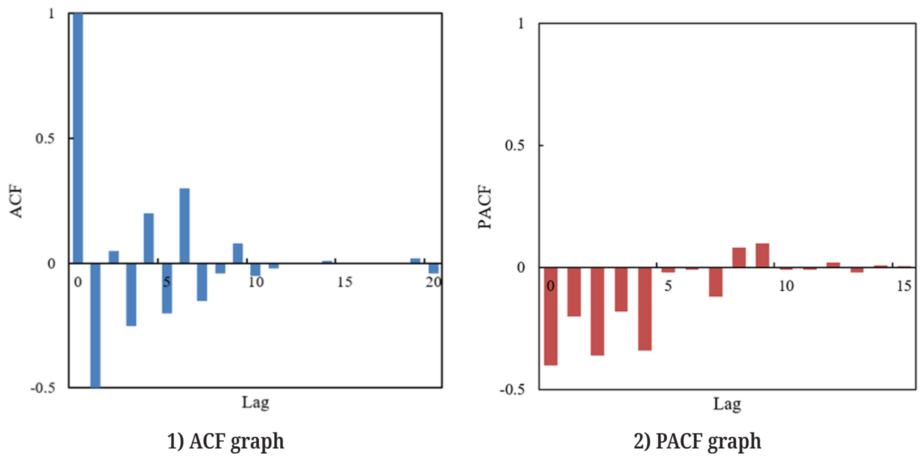

Fig. 5. Examples of ACF and PACF for emotional value series in blended learning interactions

The autocorrelation function (ACF) and partial autocorrelation function (PACF) are essential tools for analyzing time series data. In the provided ACF and PACF data, the *lag* value represents a time delay, and the ACF and PACF values indicate the correlation at different time points (see Figure 5). From the ACF graph, it is observed that at lag 0, the ACF is 1, indicating a perfect correlation with itself. As lag increases, the values of the AFC quickly decline and exhibit some fluctuations. Especially at *lag* 5 and *lag* 10, the ACF values are –0.5 and 0.3, respectively. These values indicate relatively strong negative and positive correlations, showing non-linear relationships between the series data at different times. Furthermore, ACF values gradually approach zero after *lag* 15, indicating a lower correlation over longer time intervals and demonstrating the short-term periodicity of the time series. In the PACF graph, the data show a similar trend. At *lag* 0, the PACF value is –0.4. However, subsequent fluctuations are smaller, indicating that direct correlations are primarily concentrated within a shorter range. Notably, PACF values gradually stabilize around zero at *lag* 10, suggesting that the emotional features of blended learning interactions exhibit strong short-term autocorrelation and some periodicity. However, overall, these features show weaker correlations with emotional features over longer time spans. These findings demonstrate that the research method employed in this paper effectively captures and analyzes the autocorrelation and periodicity of emotional changes in blended learning. This further supports the effectiveness of research in developing a blended learning model based on emotional analysis and provides a scientific basis for emotional analysis using mobile interactive technology in the educational field.

5 CONCLUSION

This paper explores the application of mobile interactive technology to support emotional interaction analysis in blended learning. The study focuses on the selection of emotional sensing nodes and the effective extraction of emotional features. Based on this, a highly adaptive and interactive blended learning model is constructed. The main findings include that the number of sensing nodes increases with the number of iterations, showing improved capabilities for capturing and processing emotional data; data processing efficiency increases with the number of iterations, especially where the method proposed in this paper performs better than traditional methods; the improved feature selection algorithm significantly enhances the accuracy of classifiers, particularly in handling data of different dimensions; Analysis of teacher-student interaction behaviors in blended learning shows that the use of mobile interactive technology promotes more frequent and diverse forms of interaction; ACF and PACF analyses reveal the time-dependent and periodic characteristics of the series of learning interaction emotional values.

The value of the research lies in providing a systematic perspective and specific methods for utilizing mobile interactive technology to enhance teaching and learning processes in blended learning environments, especially in comprehending and analyzing emotional interactions. This is important for designing more effective educational technology solutions and enhancing the engagement and learning outcomes of educational activities.

However, the limitations of the study are primarily reflected in the sample size and the control of environmental factors in the experiments. Due to constraints on specific learning environments and participants, the generalizability and transferability of the results may be impacted. Future research could validate the methods and conclusions of this study in a broader range of educational settings. It could also explore additional types of emotional sensing nodes and algorithms to further optimize the capture and analysis efficiency of emotional data. Additionally, future studies should consider integrating a wider variety of teaching activities and learning behavior data to comprehensively assess and enhance the educational effectiveness and application potential of blended learning models.

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