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Optimization of Teacher-student collaborative Teaching Mode Based on biological sensing Technology

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SUMMARY: *The development of bio-sensing technology provides new technical support for classroom teaching state recognition and collaborative process regulation. Focusing on the problems of feedback lag, insufficient state judgment accuracy and insufficient collaborative adjustment in teacher-student collaborative teaching, this paper constructs an optimization framework of teacher-student collaborative teaching based on biological perception technology, and integrates heart rate, heart rate variability, electroskin response, EEG attention features, classroom behavior logs and learning platform data into a unified analysis process. A total of 124 students from two natural classes were selected to carry out the 12-week quasi-experiment, including 62 students in the experimental group and 62 students in the control group. The results showed that the final test score of the experimental group was 86.37, higher than that of the control group (81.14). The score of classroom project was 88.52, higher than 82.63 of the control group; The learning satisfaction was 4.46. Research shows that this model can improve the accuracy of classroom state recognition, optimize teachers 'feedback path, and promote the transformation of teacher-student collaborative teaching from experience regulation to data-driven improvement.*

KEYWORDS: *bio-sensing technology; Teacher-student collaborative teaching; Multimodal learning analysis; Optimization of Teaching Mode*

1 Introduction

In recent years, the application of bio-sensing technology in educational scenarios has been expanded. Technologies represented by wearable devices, heart rate variation monitoring, electrodermal response recognition, EEG signal acquisition, and multimodal learning analysis are changing the way classroom teaching processes are observed. Traditional classroom mainly relies on teacher experience, student questionnaires and stage scores to judge learning status. This method can reflect part of teaching results, but it is difficult to timely capture the changes in students 'attention fluctuations, emotional stress, cognitive load and collaborative participation in the learning process. Through the continuous collection of learners' physiological signals and behavior data, bio-sensing technology provides a more fine-grained data basis for classroom state recognition, and also makes the teacher-student collaborative teaching gradually shift from experience-driven to data-driven and intelligent regulation [1-3].

Teacher-student collaborative teaching emphasizes teacher guidance, student participation, peer interaction and process feedback. Its core does not lie in simply increasing classroom activities, but in forming a teaching relationship of continuous interaction, co-construction

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and dynamic revision. In actual teaching, teachers often need to pay attention to knowledge teaching, classroom organization, student feedback and learning difficulty identification at the same time. When facing a large number of classes with large differences, it is difficult to accurately judge the collaboration quality and cognitive state of each group of students. Although some students appear to participate in the discussion, they may be in a state of low engagement or high pressure. Some students have good performance, but lack active expression and deep understanding in the collaboration process. If the teaching regulation still stays at the level of after-class analysis and subjective observation, the timeliness, pertinence and continuous optimization ability of teacher-student collaboration will be limited.

Previous studies have shown that wearable devices and multimodal learning analysis can be used for student engagement detection, emotion recognition, stress monitoring and collaborative learning state analysis, which provides new method support for educational data mining [4-6]. However, most of the existing researches focus on the identification of a single physiological indicator or the prediction of learning state, and few of them embed biometrics into the complete teacher-student collaborative teaching process. How to integrate heart rate, electrodermal, electrobrain, classroom behavior and learning results, how to transform model output into understandable and executable teaching regulation suggestions for teachers, and how to realize intelligent feedback in the classroom under the premise of protecting privacy and ethical boundaries are still problems that need to be deeply solved in current research.

Based on this, this paper focuses on the logical chain of "biological perception - state recognition - teaching feedback - collaborative optimization", and constructs the optimization framework of teacher-student collaborative teaching mode based on biological perception technology. The framework introduces computer data collection, feature fusion, machine learning classification and visual feedback mechanism into the classroom teaching process, focuses on analyzing the relationship between students 'physiological state, collaborative behavior and learning effect, and validates the promotion effect of this model on classroom participation, collaboration quality and learning effect through teaching experiments. This paper aims to provide an optimization path for classroom teaching in colleges and universities with both technical support and practical applicability, and promote the teacher-student collaborative teaching from result evaluation to process perception and dynamic improvement.

2 Related Research

2.1 Application of bio-sensing technology in educational scenarios

In recent years, bio-sensing technology has gradually extended from the fields of medical health, motion monitoring and emotion computing to educational scenarios, which provides a new data source for classroom learning state recognition. Khosravi et al. pointed out that wearable sensors can record the heart rate, activity intensity and behavioral rhythm of students in the learning process, and can be combined with learning platform data to analyze learning engagement and learning support needs [1]. Johnson et al. used wearable technology to identify students' anxiety states, and thought that physiological indicators could supplement the shortcomings of traditional questionnaires in immediacy and continuity, and provide auxiliary basis for teachers to find potential learning stress [2]. Fretes et al. used smart watches to monitor teachers' pressure changes under different teaching activities, environmental conditions and curriculum arrangements, indicating that bio-sensing technology is not only suitable for analyzing students' status, but also can reflect teachers' physiological load in classroom organization [3]. Francisti et al. further identified the relationship between the change of center rate in the teaching process and classroom activities, indicating that there was a quantifiable association between teaching behavior, classroom rhythm and teachers' physiological state [4].

With the development of artificial intelligence methods, single physiological signal recognition has gradually turned to multi-source data fusion. Pinge et al. pointed out in their review of stress detection that wearable devices combined with machine learning models can improve the stability of stress state recognition, but different devices, sampling frequencies and individual differences still affect the generalization ability of the model [5]. Younis et al. systematically summarized the application of machine learning in human emotion recognition, and argued that the joint modeling of heart rate, electrodermal, electroencephalogram, facial expression and speech features was helpful to improve the accuracy of emotional state judgment [6]. From the perspective of emotion recognition and artificial intelligence, Khare et al. proposed that future research needs to pay more attention to multimodal feature fusion, model interpretability and real scene adaptability [7]. In educational scenarios, Moise et al. constructed a deep learning model based on few-channel EEG signals, providing a lightweight technical path for classroom attention, emotion and cognitive state recognition [8]. Booth et al. pointed out from the perspective of learning engagement detection that engagement can not be explained by a single behavioral indicator, but should be comprehensively judged by combining physiological, behavioral and contextual information [9]. It can be seen that bio-sensing technology is driving educational evaluation from static result analysis to process state perception.

2.2 Theory and practice of teacher-student collaborative teaching

Teacher-student collaborative teaching emphasizes the combination of teacher guidance, student participation, peer interaction and continuous feedback, and its effective operation depends on the timely identification and dynamic regulation of multi-agent states in the classroom. Aoyama Lawrence and Weinberger proposed the framework of emotional synchronization and cognitive synchronization in collaborative learning, and believed that the rhythm consistency, emotional response and cognitive coordination between learners would affect the quality of collaboration [10]. Nguyen et al. combined the analysis of social sharing regulation and physiological arousal events, and found that common physiological reactions would appear in the process of learning group collaboration, which could be used as an important clue to understand group regulation behavior [11]. Lamsa et al. further investigated the relationship between learners' language alignment and physiological synchronization, and pointed out that certain trigger events would prompt students to share regulation, thereby changing the promotion mode of collaborative learning [12]. These studies show that teacher-student collaboration is not only the adjustment of classroom activities, but also the common change of emotion, cognition and interaction rhythm.

Multimodal learning analysis provides computer technology support for teacher-student collaborative teaching. Ouhaichi et al. systematically sorted out the research trend of multimodal learning analysis and pointed out that educational data collection has expanded from learning logs to multiple dimensions such as eye movement, voice, posture, physiological signal and interaction records [13]. Alwahaby et al. emphasized that although multimodal learning analysis can improve teacher decision-making and learning support, it must deal with ethics, privacy and data interpretation risks simultaneously [14]. Ochoa et al. proposed that the value of multimodal learning analysis does not lie in simply stacking data, but in the closed-loop process of collection, synchronization, modeling, interpretation and feedback around clear teaching problems [15]. Lee-Cultura et al. conducted research on teacher dashboard and pointed out that visualization system can help teachers understand classroom interaction and learning status, but the interface design needs to avoid information overload and transform model output into executable teaching suggestions [16]. Therefore, the key to introducing bio-sensing technology into teacher-student collaborative teaching is not only to "collect data", but also to establish an operational mechanism from state recognition to teaching intervention.

2.3 Deficiencies of existing studies

Although the existing research has laid the foundation for the improvement of education supported by biometrics sensing technology, the systematic research on the optimization of teacher-student collaborative teaching mode is still insufficient. Acosta et al. used multimodal learning analysis to predict student satisfaction in collaborative game learning, and showed that behavioral, physiological and interaction data could explain differences in collaborative experience. However, their research scenarios were biased towards specific tasks, and the teaching regulation process for conventional classrooms had not been formed [17]. Patidar et al. proposed a large-scale learning analysis system for real classroom, which proves the practical feasibility of classroom data analysis. However, the system pays more attention to classroom observation and analysis efficiency, and the deep integration of biological sensing data and teacher-student collaboration mechanism is still insufficient [18]. Corza-Vargas et al. discussed the ethics, privacy, design and cultural issues of cognitive-emotional state visualization in online learning from the perspective of students, suggesting that relevant systems should not ignore students' acceptance of data display, state labels and algorithm judgments [19]. Glasserman-Morales et al. review on the teaching application of wearable devices shows that the existing research mostly focuses on device usability, learning behavior monitoring and health state observation, and there is still a lack of full discussion on the reconstruction of teaching mode, teachers' decision support and long-term learning effect verification [20].

Table 1 summarizes the related studies. It can be seen that there are three main shortcomings in the current research. First, the application of technology is scattered, and biological sensing data is often used for the single point recognition of stress, emotion or participation, which lacks the combination with the whole process of teacher-student collaborative teaching. Second, there is a transformation fault between the model output and teachers 'teaching decisions. Some studies can complete the state classification, but it is difficult to explain how teachers should adjust the grouping, questioning, feedback and task difficulty accordingly. Third, ethics and privacy issues have not been designed synchronously with classroom application mechanisms, and students' feelings about physiological data collection, state visualization, and algorithm evaluation may still affect system acceptance. Based on this, this paper integrates biological sensing data collection, multi-modal feature fusion, classroom status recognition, teacher feedback dashboard and collaborative teaching regulation into the same framework, trying to build a strong operability of teacher-student collaborative teaching optimization model.

Table 1: Comparison of studies related to biosensing and multimodal learning analysis

Reference	Method or technique	Application scenario	Main findings	Limitations
Khosravi et al. [1]	Wearable sensors and learning analytics	Learning support in higher education	Can record learning engagement and behavioral rhythms	Insufficient discussion of classroom collaboration mechanisms
Johnson et al. [2]	Anxiety monitoring with wearable devices	Identification of students' psychological states	Helps detect learning anxiety	Focuses on individual emotions and lacks instructional feedback design
Fretes et al. [3]	Stress monitoring with smartwatches	Analysis of teachers' instructional stress	Teaching activities are related to teacher stress	Does not form a joint teacher-student regulation mechanism
Moise et al. [8]	Few-channel EEG deep learning model	Educational emotion recognition	Shows potential for lightweight application	Limited consideration of interference factors in real classroom settings
Nguyen et al. [11]	Physiological arousal and shared regulation analysis	Collaborative learning	Physiological synchrony can reflect group regulation	Limited sample size and application scenarios
Lee-Cultura et al. [16]	Multimodal teacher dashboard	Teacher classroom decision support	Enhances teachers' understanding of learning states	Needs to address information overload and the transformation of suggestions into actions
Acosta et al. [17]	Multimodal learning analytics prediction model	Collaborative game-based learning	Can predict collaboration satisfaction	Narrow task scenario, with transferability requiring further validation

3 Methods

3.1 The framework design of teacher-student collaborative teaching driven by biological perception

Based on the biosensitive technology, learning analysis theory and teacher-student collaborative teaching mechanism, this paper constructs the optimization framework of teacher-student collaborative teaching driven by biosensitive. The framework does not simply embed wearable devices or sensors into the classroom, but integrates students' physiological states, classroom behaviors, collaborative interactions and learning results into a unified data processing chain, and completes state recognition and teaching feedback generation through computer models. The core goal is to transform the attention input, emotional stress, cognitive load and collaborative participation states that are difficult to observe directly in the classroom into teaching information that can be analyzed, interpreted and fed back, so as to help teachers adjust teaching rhythm, task difficulty and collaboration organization mode in time. The overall framework is shown in Figure 1.

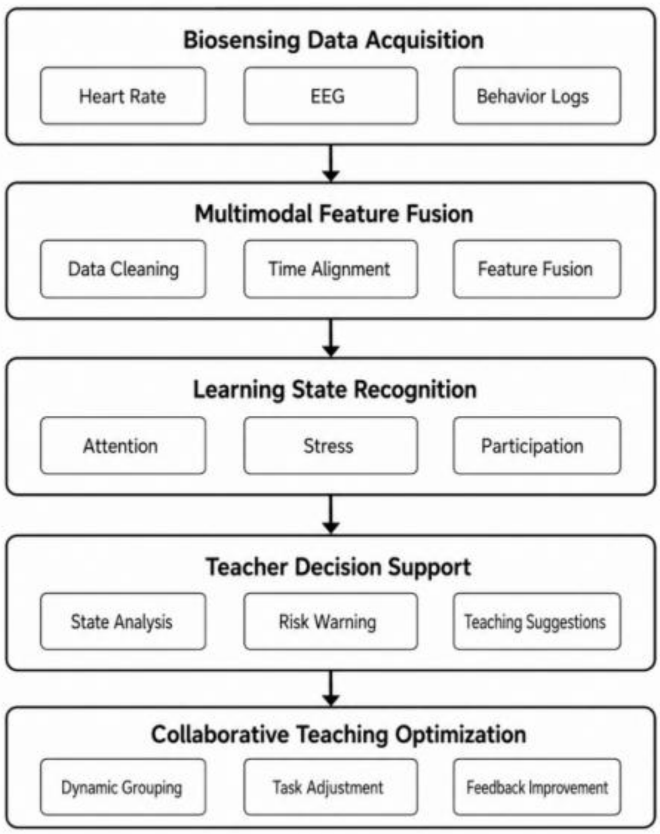

Figure 1: Framework of collaborative teaching and learning optimization driven by biological perception

The framework constructed in this paper consists of a biological sensing data acquisition layer, a multi-modal feature fusion layer, a learning state recognition layer, a teacher decision support layer, and a collaborative teaching optimization layer. The front-end data collection provides the basis for state recognition, and the model analysis results are fed back to the teacher through the visual method, and then the teacher adjusts the teaching strategy according to the actual situation of the classroom, so that the teacher-student collaborative teaching turns from experience judgment to dynamic optimization with the help of data.

The bio-sensing data collection layer is responsible for acquiring multi-source data in the classroom teaching process. The collection content included students' heart rate, heart rate variability, electrodermal response, EEG attention characteristics, class speech frequency, group interaction frequency, learning platform operation record and task completion. Let the original sensing data of the s-th student in the t-th time window be $B_{s,t}$, which can be expressed as follows.

$$B_{s,t} = \{HR_{s,t}, HRV_{s,t}, EDA_{s,t}, EEG_{s,t}, A_{s,t}, L_{s,t}\} \tag{1}$$

Here, $\mathrm{HR_{s,t}}$ represents heart rate, $\mathrm{HRV_{s,t}}$ represents heart rate variability, $\mathrm{EDA_{s,t}}$ represents electrodermal response, $\mathrm{EEG_{s,t}}$ represents EEG related features, $\mathrm{A_{s,t}}$ represents classroom behavior data, and $\mathrm{L_{s,t}}$ represents learning platform logs. This layer can continuously record the state changes of students in collaborative learning, and make up for the shortcomings of traditional questionnaire and after-class performance feedback lag.

The multi-modal feature fusion layer is used to solve the differences in sampling frequency, dimensional standard and noise level of data from different sources. The system performs time alignment, outlier removal, sliding window segmentation and standardization on the collected data, and converts physiological signals, classroom behaviors and learning performance into a unified feature vector. Let the standardized physiological characteristics be $\mathrm{P_{s,t}}$, the classroom behavior characteristics be $\mathrm{A'_{s,t}}$, and the learning performance characteristics be $\mathrm{R_{s,t}}$. The fused state characteristics can be expressed as follows.

$$\mathrm{F_{s,t}} = \mathrm{Concat}(\mathrm{P_{s,t}}, \mathrm{A'_{s,t}}, \mathrm{R_{s,t}}) \tag{2}$$

where Concat(·) represents the feature concatenation function. Through this processing, the system can avoid excessive influence of single index on classroom state judgment, and also reduce the recognition bias caused by individual physiological differences.

The learning state recognition layer completes student state analysis based on fusion features. In this paper, the classroom collaboration state is divided into four dimensions of attention input, cognitive participation, interaction level and stress degree, and the state results of students in different time Windows are output by the machine learning classification model. The comprehensive learning state score of the s-th student in the t-th time window is defined as follows.

$$\mathrm{S_{s,t}} = \mathrm{w_1E_{s,t}} + \mathrm{w_2C_{s,t}} + \mathrm{w_3I_{s,t}} - \mathrm{w_4P_{s,t}^{stress}} \tag{3}$$

Here, $\mathrm{E_{s,t}}$ represents the level of attention engagement, $\mathrm{C_{s,t}}$ represents the level of cognitive engagement, $\mathrm{I_{s,t}}$ represents the level of collaborative interaction, $\mathrm{P_{s,t}^{stress}}$ represents the degree of stress, and $\mathrm{w_1, w_2, w_3, w_4}$ are the weight coefficients. If a student continues to have a state of low engagement, high pressure or low interaction, the system will mark him as an object that needs attention to provide a basis for teacher intervention.

The teacher decision support layer converts the model output into visual feedback. The system helps teachers understand the overall classroom status and individual differences through classroom status heat map, group collaboration quality map, student status trend curve and risk warning information. When the system identified that most students had increased pressure and decreased interaction in a certain teaching link, teachers could slow down the teaching rhythm and increase case explanation or hierarchical prompts. When a group interacts frequently but the task completion quality is low, teachers can judge that their collaboration stays at the surface discussion, and guide students to carry out deep analysis through the problem scaffold. Thus, the model results do not directly substitute for teacher judgments, but provide teachers with more timely classroom evidence.

The collaborative teaching optimization layer adjusts teaching strategies according to the state recognition results and teacher feedback. The optimization contents included dynamic grouping, task difficulty adjustment, classroom questioning rhythm control, teacher tour path arrangement, peer assessment organization and after-class personalized support. Let the collaboration quality of the g-th learning group in the TTH time window be $\mathrm{Q_{g,t}}$, which can be expressed as follows.

$$Q_{g,t} = \lambda_1 \overline{S}_{g,t} + \lambda_2 D_{g,t} + \lambda_3 R_{g,t} \tag{4}$$

Here, $\overline{S}_{g,t}$ represents the average learning state of group members, $D_{g,t}$ represents the balance degree of interaction within the group, $R_{g,t}$ represents the quality of task completion, and $\lambda_1, \lambda_2, \lambda_3$ are the regulation coefficients. The system generates teaching regulation suggestions according to the change of collaborative quality, so that classroom collaboration no longer depends on a single experience judgment, but forms a continuous improvement mechanism based on data evidence.

3.2 Research object and design of teaching experiment

The research implementation process was carried out in sequence according to research object determination, experiment grouping, system deployment, teaching intervention, data collection and effect evaluation, and the overall process was shown in Figure 2. The design adopted the idea of quasi-experimental research, and verified the teacher-student collaborative teaching model driven by biological perception in the classroom under the premise of ensuring the relatively real teaching situation.

Subjects: Two second-year natural classes of educational technology related courses in a local undergraduate college were selected as the research subjects, with a total of 124 students. Among them, 62 were in the experimental group and 62 in the control group. The students in both groups had completed the prerequisite courses of educational psychology and information-based teaching foundation, and had the basic ability to participate in collaborative learning and use online learning platforms. Before the experiment, students' course grades in the previous semester, learning engagement questionnaire, classroom collaboration ability scale and familiarity with information technology use were pre-tested. The results of independent sample t-test showed that there were no significant differences in the basic performance, collaboration ability and learning engagement between the two groups ($p > 0.05$), indicating that the two groups of samples were comparable. The sample grouping can be expressed as follows.

$$N = N_e + N_c = 62 + 62 = 124 \tag{5}$$

where N denotes the total sample size, N_e denotes the number of experimental group and N_c denotes the number of control group. To further test the baseline differences between the two groups, standardized differences are calculated as follows:

$$D_b = \frac{|\bar{X}_e - \bar{X}_c|}{\sqrt{(SD_e^2 + SD_c^2)/2}} \tag{6}$$

Here, $\bar{X}_e$ and $\bar{X}_c$ represent the pre-test mean of the experimental group and the control group, respectively, and SD_e and SD_c represent the standard deviation of the two groups, respectively. When $D_b<0.10$, the two groups were considered to have high equilibrium before the experiment. After calculation, the D_b of basic performance, learning engagement and collaboration ability were 0.07, 0.06 and 0.08, respectively, which met the requirements of subsequent comparative analysis.

Experimental design: This study used a quasi-experimental design lasting 12 weeks, with 90 minutes of classroom instruction scheduled twice a week. The two groups were taught by the same teacher, using the same teaching materials, teaching progress, teaching objectives and assessment standards. The experimental group adopted the teacher-student collaborative teaching model driven by biological perception, and introduced wearable devices, classroom behavior collection procedures, learning platform logs and teacher visualization dashboards in the process of collaborative tasks. Teachers adjusted the grouping method, task difficulty, questioning rhythm and classroom support path according to the system feedback. The control group adopted the conventional teacher-student collaborative teaching mode, and teachers mainly adjusted teaching according to classroom observation, student speech and completion of stage assignments, without using biosensing data feedback.

The teaching process of the experimental group included four links: pre-class status filing, real-time perception in class, classroom collaborative regulation and feedback correction after class. In the pre-class stage, the system recorded students' basic learning portraits, including pre-test scores, learning habits and collaboration preferences. In the middle stage of class, the system collected students' heart rate, heart rate variability, electrodermal response, classroom interaction frequency and learning platform operation behavior. In the classroom control stage, teachers adjusted teaching activities according to the class state heat map and group collaboration tips. In the after-class phase, the system generates student status reports and group collaboration quality reports for the next round of instructional design. The control group similarly completed pre-class tasks, in-class collaboration, and after-class assignments, but did not receive real-time biosensing feedback.

In order to measure the effect of teaching intervention, this paper sets up four evaluation indicators: learning performance improvement rate, classroom participation, collaboration quality and learning satisfaction. The improvement rate of academic performance is defined as:

$$\mathrm{G}=\frac{\mathrm{Score_{post}}-\mathrm{Score_{pre}}}{\mathrm{Score_{pre}}}\times 100\% \tag{7}$$

Here, $\mathrm{Score_{post}}$ represents the pre-test score, $\mathrm{Score_{pre}}$ represents the post-test score, and G represents the improvement rate of student academic performance. Classroom participation was comprehensively calculated by the number of speeches, the timeliness rate of task submission, the frequency of interaction and the number of effective platform operations. Collaboration quality was composed of contribution balance, discussion depth, task completion quality and peer assessment results. Learning satisfaction was measured using a 5-level scale. After the experiment, the average score of the experimental group increased from 76.48 points to 86.37 points, and the control group increased from 75.92 points to 81.14 points. The mean value of classroom participation in the experimental group was 88.26%, which was higher than 79.43% in the control group. The collaborative quality score was 4.31 in the experimental group and 3.82 in the control group. The above data are used for subsequent result analysis and are not the only basis for judging the teaching effect.

System deployment: The classroom deployment of the experimental group consists of four parts: wearable perception end, classroom data collection end, background analysis end and teacher feedback end. The wearable sensing end used a wrist-worn sensor to collect heart rate, heart rate variability and electrodermal signal, and the sampling interval was set to 5 seconds. The classroom data collection terminal recorded student speech, task submission, page stay, resource click and group interaction behavior. The background analysis was based on Python 3.11, PyTorch 2.2 and PostgreSQL 14 to complete data storage, feature processing and state recognition. The teacher feedback end presents heatmaps of class status, group collaboration quality changes, and student risk tips in the form of Web dashboard. The system interface uses RESTful architecture, the front-end and back-end transmit data through HTTPS, and the classroom data is automatically synchronized according to the time window.

Ethics and Data Safety: Before starting the experiment, the research team explained the data collection type, scope of use, and withdrawal mechanism to the students, and obtained informed consent. All biosensing data are stored in a numbered manner and do not directly display student names. The teacher-side dashboard presents only the status information needed for instructional support and does not use physiological status labels for grade punishment or public ranking. Data access was limited to the research team and the class instructor, and the original physiological data were desensitized and archived after the experiment. In order to avoid additional pressure caused by wearing the device, students were allowed to pause wearing the device when they were unwell or their personal wishes changed during the study, and their classroom learning rights and interests were not affected.

Figure 2: Research implementation process

Figure 2 shows that this study did not use the bio-sensing technology as an isolated classroom monitoring tool, but embedded it in the complete process of the teaching experiment. The research objects, teaching content, teacher factors and evaluation criteria were relatively consistent, and the experimental differences mainly came from whether to introduce biological sensing data feedback and computer-aided decision-making mechanism into the teaching model. This design can clearly test the actual effect of biosoncept technology on teacher-student collaborative teaching optimization, and provide reliable data basis for subsequent teaching effect analysis。

3.3 Biosensing data collection and teaching effect analysis

(1)Data acquisition

The data collection of this study was carried out around four types of information: learning results, classroom process, biological perception signal and subjective experience, so as to ensure that the evaluation of teaching effect could not only reflect the change of performance, but also show the state difference in the process of teacher-student collaboration. The learning outcome data included pre-test scores, stage task scores, class project ratings, and post-test scores. The pre-test was used to judge the basic level of the two groups of students, and the post-test was used to measure the learning effect after the teaching intervention. The classroom projects were scored independently by two teachers with more than five years of teaching experience, and the scoring dimensions included task completion, scheme rationality, collaborative contribution, and expression quality. The agreement between the two raters was tested using Cohen's κ coefficient, and the result was 0.84, indicating that the manual rating had high reliability.

Biosensing data are mainly obtained from wrist-worn sensors and lightweight EEG acquisition devices. Heart rate, heart rate variability, and galvanic skin response were recorded by a wrist-worn device with a sampling interval of 5 seconds. Eeg devices recorded attention-related features and cognitive load changes, and the sampled data were aggregated according to a 30-second time window. The classroom behavior data were collected by the classroom observation system and the learning platform background, including the number of speeches, the frequency of group interaction, the time of task submission, the number of resource clicks, the length of page stay and online discussion records. The subjective experience data were obtained through the Learning Engagement Scale, the Collaborative Satisfaction Scale, and the Cognitive Load scale, all using a 5-point scoring method.

In order to ensure that the data from different sources can enter the unified analysis process, the system cleaned, aligned and anonymized the original data after collection. Missing fields, abnormal timestamps, duplicate logs, and physiological data that are significantly outside the normal range of the device are eliminated. Time records generated by different devices are uniformly converted into millisecond timestamps. Student identity information is replaced with random hash coding. Let the original features of class m mode at student s and time window t be $x_{m,s,t}$, and the normalized result is as follows.

$$Z_{m,s,t} = \frac{x_{m,s,t} - \mu_m}{\sigma_m} \tag{8}$$

Here, μ_m represents the mean value of the m-th modal feature, σ_m represents the corresponding standard deviation, and $Z_{m,s,t}$ represent the standardized features after eliminating the influence of dimension. This processing can reduce the difference in the value range of heart rate, electrodermal, EEG and behavior log, so that the subsequent model can recognize the classroom state more stably.

In the feature extraction stage, the system transformed the standardized physiological signals, classroom behaviors and learning task data into computable indicators, including average heart rate change rate, heart rate variation stability, skin pulse fluctuation intensity, attention level, interaction density, task completion timeliness rate and resource usage depth.

The class participation index is defined as:

$$\mathrm{CI_s} = \frac{\mathrm{a_1F_s + a_2T_s + a_3U_s + a_4M_s}}{\mathrm{a_1 + a_2 + a_3 + a_4}} \tag{9}$$

Among them, $\mathrm{CI_s}$ represents the classroom participation index of the S-th student, $\mathrm{F_s}$ represents the frequency of classroom speech and interaction, $\mathrm{T_s}$ represents the timeliness rate of task submission, $\mathrm{U_s}$ represents the effective use of learning platform, $\mathrm{M_s}$ represents the contribution degree of group collaboration, $\mathrm{a_1, a_2, a_3, a_4}$ are the index weights. Through this index, the system can transform the scattered classroom behavior into a continuous level of participation, and provide a quantitative basis for the comparison between the experimental group and the control group. Figure 3 shows the data processing flow.

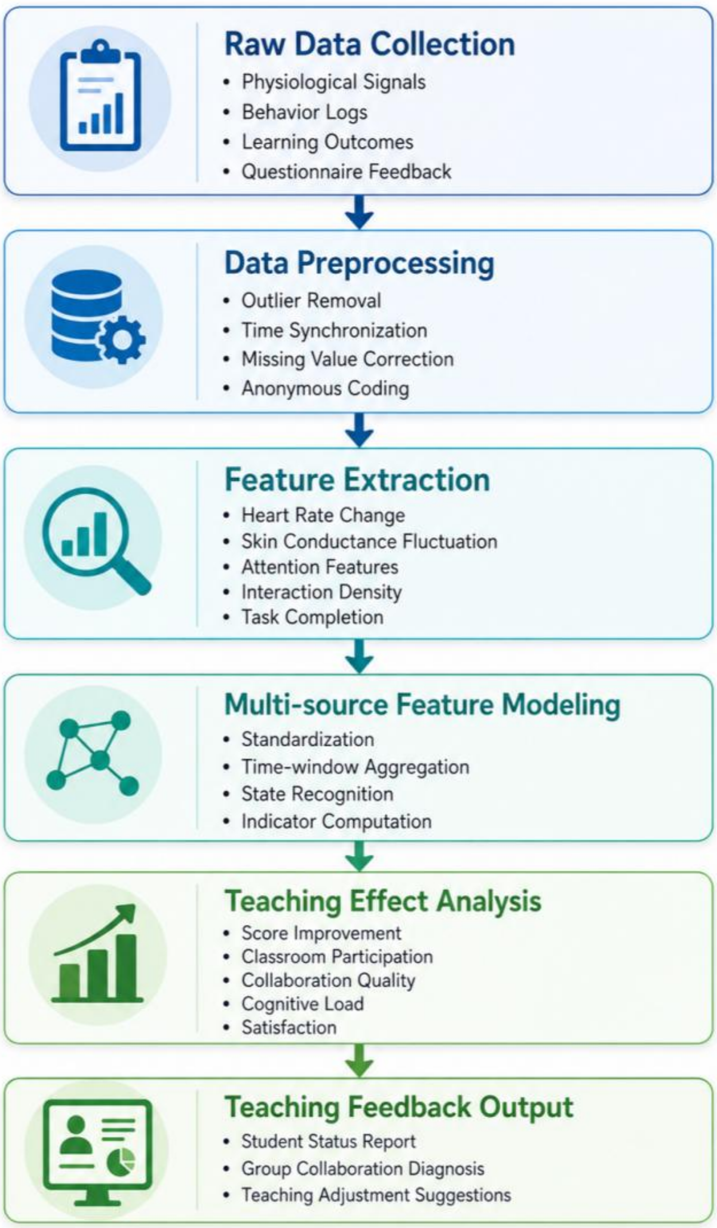

Figure 3: Process of biological sensing data processing and teaching effect analysis

(2)Data analysis

Data analysis was done using Python 3.11 and SPSS 26.0. Python for data cleaning, feature extraction, time window aggregation, and machine learning modeling SPSS was used for descriptive statistics, independent sample t-test, paired sample t-test, and covariance analysis. In order to control the influence of pre-test scores on post-test results, this paper introduced covariance analysis into the comparison between groups, taking pre-test scores as covariates, teaching modes as independent variables, and post-test scores, classroom participation index, collaborative quality score and learning satisfaction as dependent variables. The comprehensive index of teaching effect is defined as:

$$\mathrm{E_{total}} = \mathrm{b_1G} + \mathrm{b_2P} + \mathrm{b_3Q} + \mathrm{b_4S} - \mathrm{b_5L} \tag{10}$$

Among them, G represents the grade improvement rate, P represents the classroom participation index, Q represents the quality of group collaboration, S represents the learning satisfaction, L represents the cognitive load level, and $\mathrm{b_1, b_2, b_3, b_4, b_5}$ are the weights of each index. The index is used to comprehensively judge the overall effect of the biological perception driven teaching model. Because excessive cognitive load may impair the learning experience and continuous engagement, it is represented as a negative term in the formula.

In order to further analyze the applicability of bio-sensing technology to different student groups, this paper divided students into high basic group and low basic group according to the pre-test score, and divided students into high familiarity group and low familiarity group according to the technology familiarity, and compared their performance improvement, participation index and satisfaction change respectively. This analysis is used to judge whether the system is only effective for a certain type of students and avoid the technical intervention to enlarge the classroom differences. At the same time, this paper sets up module ablation analysis to compare the changes in teaching effects under four conditions: complete mode, removal of biosensing feedback, removal of teacher dashboard, and removal of dynamic grouping suggestions. By comparing different configurations, it is possible to judge the independent contributions of biological sensing data, teacher visual feedback, and collaborative strategy regulation in mode optimization.

After the experiment, the system formed a total of about 186,000 valid physiological signal records, about 423,000 learning platform logs, 7 248 classroom interaction records, and 124 valid questionnaires after time window aggregation. After cleaning, the effective rate of the data was 94.7%. Together, these data form the basis of subsequent result analysis, which enables this paper to evaluate the teacher-student collaborative teaching model based on bio-sensing technology from three levels: achievement results, classroom process and student experience.

4 Results and discussion

(1)Comparison of learning results between the two groups

This paper compares the learning results between the experimental group and the control group from four aspects: stage test, final test, project task and comprehensive performance. The results of the two groups were close in the pre-test stage, indicating that the learning basis before the experiment was relatively balanced. After 12 weeks of teaching intervention, the experimental group showed more obvious improvement in all learning outcomes, as shown in Figure 4.

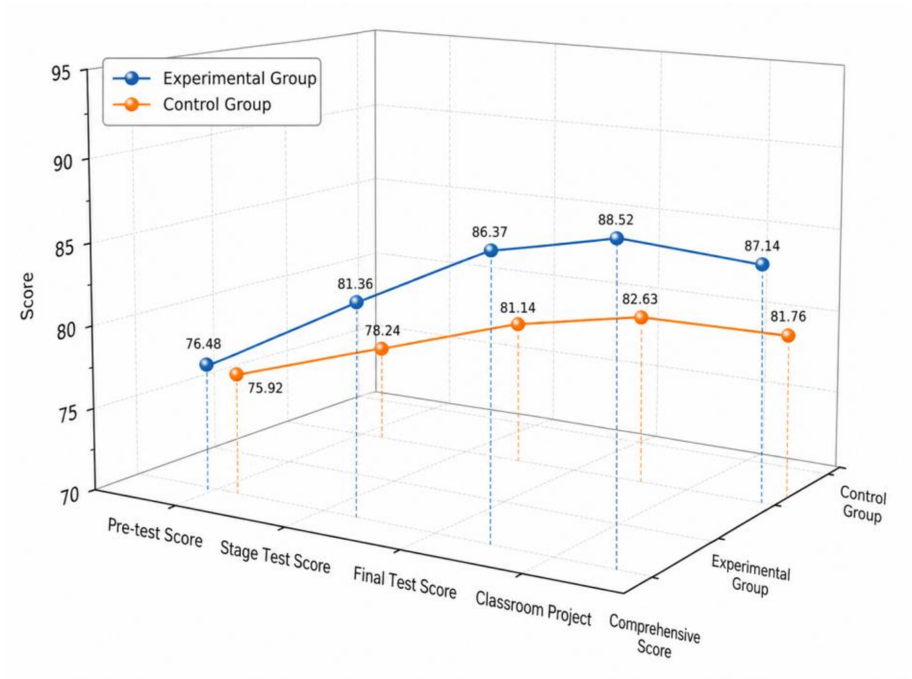

Figure 4: Comparison of learning results between experimental group and control group

Figure 4 shows that the difference between the two groups in the pre-test stage is small, and the experimental group is only 0.56 points higher. After entering the stage test, the average score of the experimental group reached 81.36, and that of the control group was 78.24, and the gap began to expand. In the final test, the average score of the experimental group was 86.37, 5.23 points higher than that of the control group; The difference in classroom project scores was more obvious, the experimental group reached 88.52 points, the control group was 82.63 points. Since the classroom project tasks were more dependent on collaborative discussion, problem analysis and process feedback, this result indicated that the teaching model driven by biological perception not only improved students 'mastery of knowledge points, but also had a positive impact on expression, division of labor and problem solving in collaborative tasks.

Further, from the perspective of learning process, the improvement of experimental group's performance did not come from simply increasing the amount of practice, but was related to classroom state feedback and teachers 'timely regulation. When the system identified that some groups showed elevated pressure, decreased interaction, or distracted attention during task advancement, the teacher was able to adjust the explanation rhythm in time, add problem scaffolds, or reallocate group roles. Although collaborative learning was also used in the control group, teachers mainly relied on on-site observation and homework to judge students' status, and there was a certain delay in feedback. Therefore, it is easier for the experimental group to form a learning path for continuous improvement in complex tasks and comprehensive projects.

(2)Changes in biological perception status and classroom participation

In order to analyze the influence of the teaching mode on the classroom process, this paper compared the changes of the attention engagement index, the pressure stability index and the collaborative interaction index of the experimental group within 12 weeks, as shown in Figure 5. The three indicators are standardized and range from 0 to 100, with higher scores indicating more positive states. Among them, the higher the pressure stability index, the smaller the student pressure fluctuation, the more stable the classroom state.

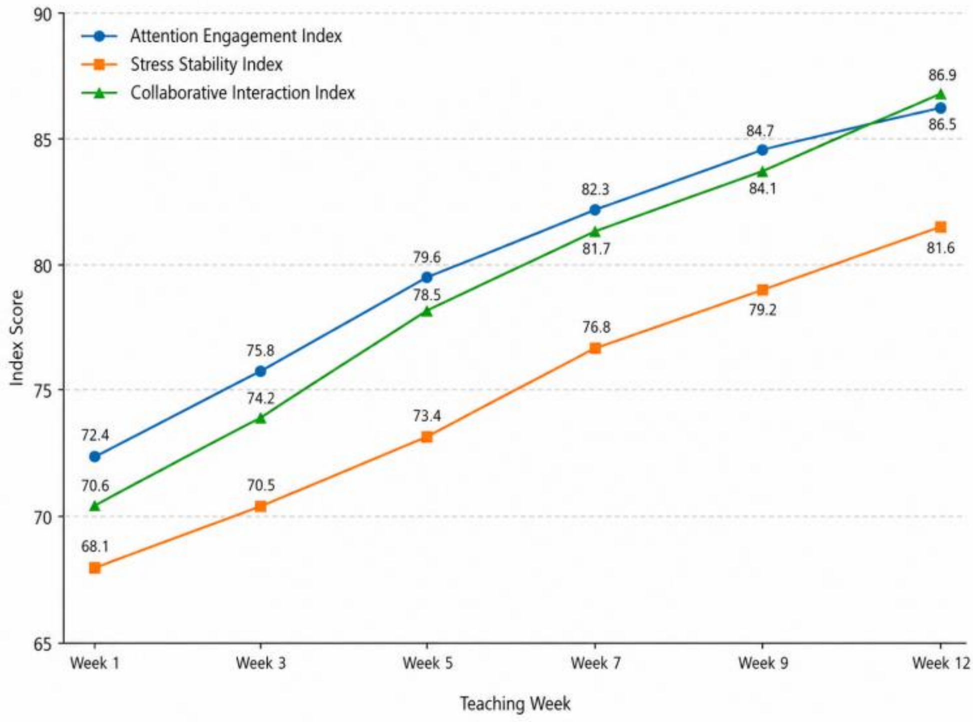

Figure 5: Variation trend of biosensing status in the experimental group

Figure 5 shows that the attention engagement index of the students in the experimental group increased from 72.4 in the first week to 86.5 in the 12th week, indicating that the degree of continuous attention of the students in the classroom tasks was significantly enhanced. The stress stability index increased from 68.1 to 81.6, indicating that students gradually adapted to data-assisted feedback and group collaboration rhythm in collaborative tasks, and the fluctuation of classroom stress was alleviated. The collaborative interaction index increased from 70.6 to 86.9, which showed a large increase, indicating that biosensing feedback did not weaken the natural communication between students, but promoted more stable group interaction through teacher regulation.

This change has a strong teaching interpretation significance. In this paper, bio-sensing technology is not used to passively monitor students, but to serve the teaching rhythm judgment. For example, if there is a decline in the attention index of the whole class in a teaching link, the teacher can pause the promotion of new knowledge and turn to case explanation or group discussion. If the pressure of a group continues to be high, the teacher can reduce the complexity of the task or provide process hints. If the interaction index is low, student participation can be improved through role assignment, problem guidance and peer review. The resulting classroom regulation mechanism makes the teacher-student collaboration shift from experiential organization to process optimization aided by data.

(3)Comparison of learning engagement and classroom behavior

The classroom behavior data further validated the changes in learning engagement in the experimental group. In this paper, the task completion rate on time, the number of effective speeches in class, the number of learning resource visits, and the group mutual assessment completion rate are selected as the participation indicators, and the results are shown in Figure 6.

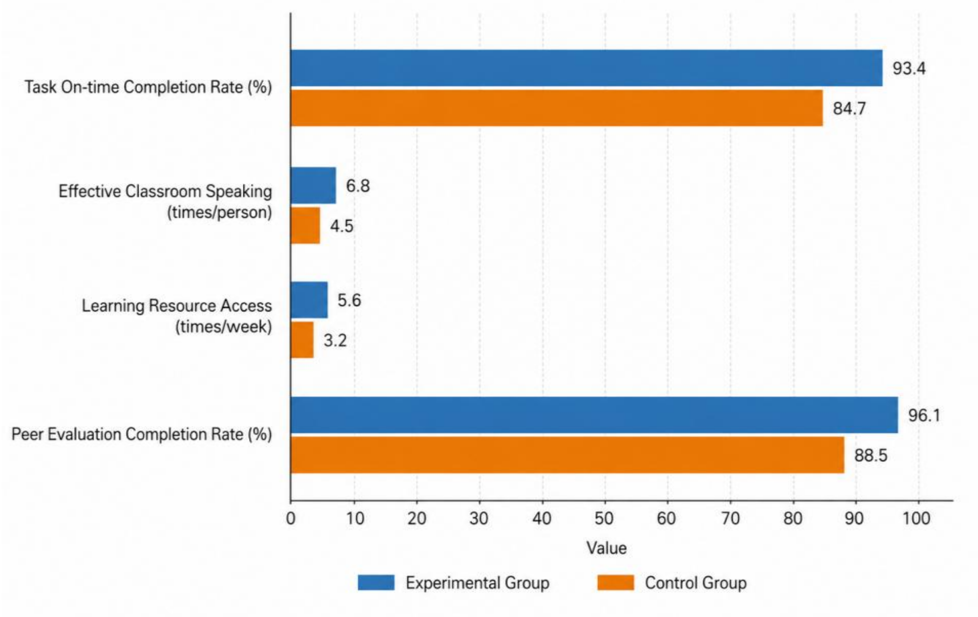

Figure 6: Comparison of classroom engagement indicators between the two groups

As can be seen from Figure 6, the task completion rate of the experimental group reached 93.4%, which was 8.7 percentage points higher than that of the control group. The number of effective speeches in class was 6.8 times/person, and 4.5 times/person in the control group. The number of visits to learning resources was 5.6 times per week and 3.2 times per week in the control group. The completion rate of mutual evaluation in the experimental group reached 96.1%, which was also higher than 88.5% in the control group. These results indicated that the biological perception driven model had a strong promotion effect on student participation behavior.

The reasons for the improvement of classroom participation in the experimental group are mainly reflected in two aspects. First, the system can help teachers find low participation students and low interaction groups, so that classroom support is more targeted. Secondly, bio-sensing data and learning platform logs together constitute a continuous feedback chain, and students 'performance in classroom tasks, resource learning and group evaluation can be recorded in time and converted into teaching basis. Compared with the traditional classroom, this model reduces the situation of "teachers are difficult to detect in time, students lack of active expression, problem feedback is delayed", so that the quality of collaborative teaching process is more fully guaranteed.

(4)Analysis of learning experience and technology acceptance

In order to evaluate students' subjective feelings on the biological perception driven teaching model, this paper conducted a questionnaire survey from five aspects of learning satisfaction, perceived usefulness, perceived ease of use, privacy security and continued use intention, and scored using a 5-level scale. The results are shown in Figure 7.

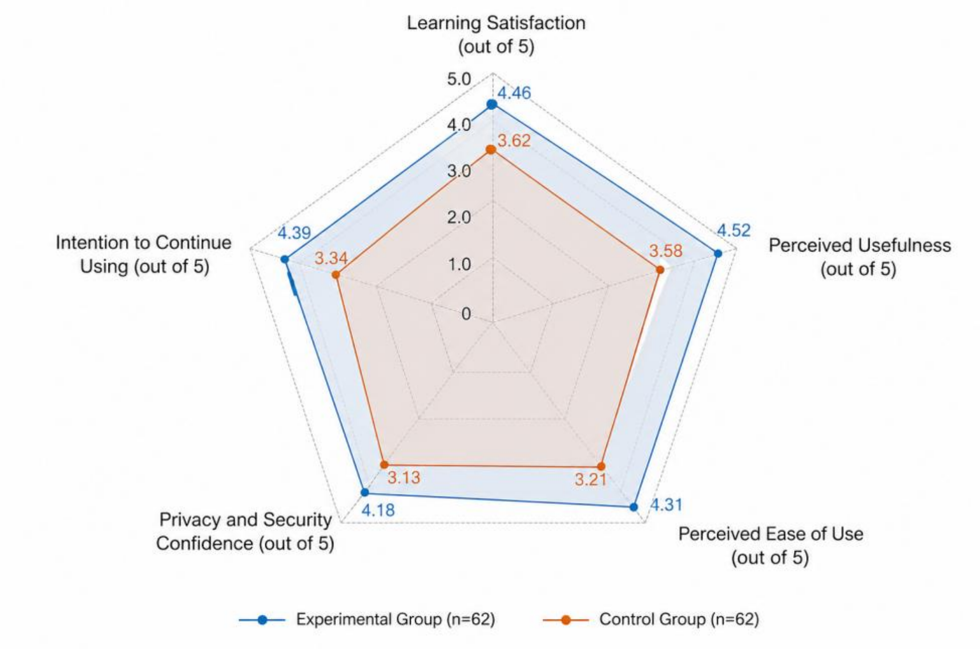

Figure 7: Results of learning experience and technology acceptance in the experimental group

Figure 7 shows that the students in the experimental group had a higher overall evaluation of the teaching model. Among them, the mean value of perceived usefulness was the highest, 4.52, indicating that students generally believed that biosensing feedback was helpful to improve classroom learning status and teacher support quality. The learning satisfaction was 4.46, and the willingness to continue to use was 4.39, indicating that students had a strong acceptance of this model. The perceived ease of use was 4.31, indicating that the process of device wearing, platform operation and classroom feedback was relatively smooth as a whole. The sense of privacy is 4.18, which is lower than other indicators, but still at a high level, indicating that students still maintain a certain cautious attitude towards physiological data collection.

This result suggests that technology effectiveness is not the only evaluation criterion when bio-sensing technology enters the classroom. If students think that there is pressure in data collection, the status label may be disclosed, or the algorithm results will affect the teacher's evaluation, their willingness to accept will be affected. Therefore, anonymized coding, permission control and non-punitive use principles are set up in the experiment, and the teacher side only presents the information required for teaching support, and does not directly incorporate biological status into the performance evaluation. This process can help to reduce students' psychological burden, and make technology really serve collaborative teaching, rather than form a new source of classroom pressure.

(5)Equity assessment of different student groups

In order to test whether this model can support students with different basic levels and different information technology proficiency, this paper divided students into groups according to pre-test scores and technology familiarity, and compared the final scores and collaboration quality between the experimental group and the control group. The results are shown in Table 2.

Table 2: Comparison of learning results of different student groups

Grouping dimension	Indicator	Experimental group mean ± SD	Control group mean ± SD	p-value	Cohen's d
High-baseline students	Final score	89.12±4.86	84.35±5.41	<0.001	0.93
High-baseline students	Collaboration quality	4.48±0.31	4.05±0.38	<0.001	1.24
Low-baseline students	Final score	83.41±5.22	77.86±5.67	<0.001	1.02
Low-baseline students	Collaboration quality	4.17±0.36	3.62±0.42	<0.001	1.41
High technology familiarity	Final score	87.92±5.03	82.38±5.49	<0.001	1.05
Low technology familiarity	Final score	84.76±5.18	78.93±5.76	<0.001	1.06
Male students	Final score	86.58±5.11	81.02±5.37	<0.001	1.06
Female students	Final score	86.21±5.04	81.28±5.43	<0.001	0.94

Table 2 shows that the experimental group outperforms the control group in different student groups. The effect size of collaborative quality of students with low foundation was 1.41, which was higher than that of students with high foundation of 1.24, indicating that the model had a more obvious support role for students with weak learning foundation. The reason is that students with low foundation are prone to silence, task avoidance or peer dependence in traditional collaborative classroom, while biosensing feedback can help teachers identify their stress and low participation status earlier, and reduce learning barriers through task stratification, problem prompts and peer support.

From the perspective of technical familiarity, the final score of students with low technical familiarity in the experimental group was 84.76 points, which was significantly higher than 78.93 points in the control group, indicating that the system did not cause obvious technical threshold. Since the teacher dashboard mainly serves for teacher decision-making, the operation of the student side is not complex, and the biological sensing device only needs to be worn in class and automatically upload data, which reduces the extra learning burden. In the dimension of gender, both boys and girls in the experimental group were significantly better than those in the control group, and the difference was not obvious within the group, indicating that the model did not show obvious gender bias within the sample range.

(6)Module contribution and ablation analysis

In order to further judge the independent contribution of each module to the teaching effect, this paper sets up four teaching configurations for ablation comparison: complete mode, removing biological perception feedback, removing teacher visualization dashboard, and removing dynamic grouping suggestions. The comparison indicators included comprehensive performance, classroom participation index, collaborative quality, and cognitive load, and the results are shown in Table 3.

Table 3: Comparison of teaching effects under different module configurations

Mode configuration	Overall score	Classroom participation index	Collaboration quality	Cognitive load
Full mode	87.14±4.72	88.26±5.13	4.31±0.34	2.61±0.28
Without biosensing feedback	83.28±5.06	82.47±5.68	4.02±0.39	3.04±0.32
Without teacher visualization dashboard	81.96±5.34	80.15±6.21	3.88±0.44	3.17±0.35
Without dynamic grouping suggestions	82.74±5.18	81.36±5.87	3.79±0.47	3.09±0.31

Table 3 indicates that the full mode performs best in all four metrics. After removing the biosensing feedback, the comprehensive score dropped to 83.28, and the classroom participation index dropped to 82.47, indicating that real-time status data was an important basis for the model to play a role. After removing the teachers' visual dashboard, the comprehensive score further decreased to 81.96, and the cognitive load increased to 3.17, indicating that the simple collection of data could not be naturally translated into teaching effects, and teachers must be able to understand and use the model results. After removing the dynamic grouping suggestions, the collaborative quality dropped to 3.79, indicating that the optimization of collaborative teaching not only depended on the teacher's explanation, but also needed to continuously adjust the group structure, role arrangement and task difficulty.

This result further indicates that the model constructed in this paper is not a simple combination of "equipment monitoring + performance analysis", but a closed-loop system composed of biological perception feedback, teacher decision support and collaborative strategy adjustment. The biological perception module provides state evidence, the dashboard completes information interpretation, and the dynamic grouping and task adjustment implement the analysis results into classroom actions. The lack of any link in the three will weaken the overall effect of the teaching model.

(7)Discussion of Results

Taking the above results into account, it can be seen that the teacher-student collaborative teaching model based on bio-sensing technology has a positive effect on learning outcomes, classroom participation, collaboration quality and learning experience. Compared with conventional collaborative teaching, the advantage of this model does not lie in replacing teachers, but in expanding the scope of teachers' perception of classroom status. In traditional classroom, teachers can only judge students 'state based on speech, expression, homework and classroom discipline, but many learning difficulties do not immediately show up as explicit behaviors. Bio-sensing data can reveal students' attention fluctuations, pressure changes, and collaborative participation differences, so that teachers can find hidden problems in the teaching process earlier.

From the perspective of teaching mechanism, the key value of this model is to construct a cyclic structure of "data identification - teacher judgment - classroom regulation - effect feedback". Data recognition improves the timeliness of classroom state judgment, teacher judgment ensures the educational rationality of teaching decision-making, classroom regulation enables the model results to enter the real teaching process, and effect feedback provides a basis for the next round of teaching optimization. Therefore, this model not only maintains the dominant position of teachers in teaching objectives, value guidance and complex situation judgment, but also gives full play to the advantages of computer models in real-time processing, multi-source fusion and trend identification. At the same time, the experimental results also suggest that the application of this model needs to grasp the boundary. Bio-sensing data is sensitive and cannot be simply used for student ranking or punitive evaluation. The recognition result of the model has the probability attribute, which can not replace the teacher's comprehensive understanding of the student's individual situation. Classroom technology deployment also needs to consider equipment cost, wear comfort, and system stability. If these problems are ignored, bio-sensing technology may be transformed from a teaching support tool to a new management pressure. Therefore, the promotion of this model should synchronize the improvement of data rights, informed consent and teacher digital literacy training, so that technical support is consistent with educational ethics.

5 Conclusion

Focusing on the problems of state recognition lag, insufficient feedback basis and inaccurate collaborative regulation in teacher-student collaborative teaching, this paper constructed an optimization framework of teacher-student collaborative teaching mode based on biological sensing technology, and verified it through a 12-week quasi-experiment. Heart rate, heart rate variability, electrodermal response, electroencephalogram attention features, classroom behavior logs and learning platform data were incorporated into the unified analysis process, forming a closed-loop mechanism of "biological sensing data acquisition - multi-modal feature fusion - learning state recognition - teacher decision support - collaborative teaching optimization". The experimental results showed that the final test score of the experimental group reached 86.37, which was higher than that of the control group of 81.14. The score of the classroom project was 88.52, higher than 82.63 of the control group. In terms of learning experience, the learning satisfaction of the experimental group was 4.46, and the perceived usefulness was 4.52, indicating that students had a high acceptance of this model. The above results showed that bio-sensing technology could provide teachers with more timely evidence of classroom status, promote task difficulty adjustment, classroom question optimization and group collaboration improvement, so as to improve the controllability and collaboration quality of teaching process.

There are still some limitations in this paper. The experimental samples are from two natural classes in the same institution, the sample size is 124 people, and the research period is 12 weeks, which is not enough to fully verify the adaptability of the model in different disciplines, different grades and long-term teaching scenarios. Biological sensing data is affected by the comfort of equipment wearing, individual physiological differences and classroom environment interference, and the model recognition results still need to be judged by teachers combined with teaching experience. In addition, physiological data is sensitive, and the boundaries of data collection, storage, visualization and use still need stricter ethical norms. Follow-up research can expand the sample scope, extend the experimental period, and carry out cross-scenario verification in different courses. At the same time, multi-modal feature fusion algorithm, lightweight device deployment method and teacher dashboard interaction design should be further optimized to reduce the cost of classroom application. In the future, privacy protection, informed consent and non-punitive evaluation mechanisms need to be improved to ensure students' rights and educational equity while improving the teaching accuracy of bio-sensing technology.

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