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The positive significance of the student-subject teaching management model to the regulation of autonomic nervous system

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SUMMARY: *Under the background of digital education, the teaching management mode is shifting from teacher leading to student main participation, and the relationship between students 'learning behavior and autonomic nervous system regulation needs to be objectively analyzed by computational methods. Aiming at the student-subject teaching management scenario, this paper integrates learning platform logs, classroom interaction records, heart rate variability, galvanic skin response and teaching feedback data, constructs multi-source state vectors, and designs feature normalization, autonomic nervous system regulation index calculation, state recognition and machine learning intervention decision-making methods. 120 undergraduates were included in the experiment, and 112 valid samples were finally retained, forming 16800 learning behavior records, 13440 physiological signal segments and 2860 teaching feedback records. The results showed that all dimensions of students 'learning autonomy were significantly improved, RMSSD increased from 31.6 ms to 42.8 ms, and LF/HF decreased from 2.15 to 1.48. The AUC of the proposed model reaches 0.962, the F1 value reaches 94.1%, and the adjusted risk status is reduced from 16.0% to 5.4%. The research can provide technical support and practical basis for the monitoring of students 'physical and mental state, intelligent teaching management and personalized intervention.*

KEYWORDS: *Student-oriented teaching management; Autonomic nervous system regulation; Heart rate variability; Machine learning*

1 Introduction

With the development of education digitization and learning analysis technology, teaching management has gradually shifted from the mode of teacher control, unified arrangement and result assessment to the dynamic management mode that pays more attention to the participation of students, learning process feedback and individual state adjustment [1]. Student-subject teaching management emphasizes the active role of students in learning goal setting, learning task selection, learning rhythm adjustment and learning feedback expression, so that teaching management no longer stays in the classroom discipline, score statistics and task completion of the external supervision level. Instead, it further focuses on students' cognitive engagement, emotional fluctuation, stress response and self-regulation ability in the learning process [2]. For students in a high-intensity learning environment, learning autonomy is closely related to the state of physical and mental regulation, and changes in teaching management methods may affect their psychological stress level, attention stability and autonomic nervous system regulation ability [3, 4].

The autonomic nervous system mainly maintains the stability of the body's internal

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environment through the synergistic effect of sympathetic and parasympathetic nerves, and plays an important role in the process of learning pressure, emotional arousal, attention concentration and fatigue recovery [5]. Physiological signals such as heart rate variability, galvanic skin response, respiratory rhythm and heart rate change can reflect the regulation state of students 'autonomic nervous system to a certain extent. Among them, heart rate variability is often used to evaluate parasympathetic nerve activity and stress recovery ability, and galvanic skin response can reflect emotional arousal and tension [6, 7]. Traditional teaching management research mostly relies on questionnaires, interviews and performance data analysis. Although it can present students' subjective experience and learning results, it is difficult to continuously and objectively depict students' physiological changes in the learning process, and it is also difficult to explain the action path of teaching management mode on students' internal adjustment mechanism [8].

Computer perception technology, wearable devices and machine learning methods provide new technical support for the research of this problem. By collecting multi-source data such as students 'classroom participation behavior, learning platform log, heart rate variability, galvanic skin response and so on, the joint representation of students 'learning state and physiological regulation state can be constructed. Through feature normalization, time series modeling, classification recognition and intervention decision algorithm, the correlation between learning autonomy change and autonomic nervous system regulation under the student-subject teaching management mode can be further analyzed [9]. Compared with relying solely on manual observation or phased evaluation, computer-based multi-source data analysis can capture the change of students 'learning status in more detail, and provide quantifiable, traceable and feedback technical basis for teaching management optimization [10].

Existing studies have discussed student teaching, learning behavior analysis and educational data mining, and some studies have used physiological signals for stress recognition, emotion analysis and learning engagement evaluation. However, the research on the relationship between the student-subject teaching management mode and the autonomic nervous system regulation is still insufficient, especially the lack of systematic analysis combining the teaching management process, physiological regulation indicators and machine learning recognition models. Based on this, this paper takes the student-subject teaching management mode as the research object, introduces learning behavior data and physiological signal data, constructs a multi-source state vector for autonomic nervous system regulation, and designs feature normalization, autonomic nervous system regulation index calculation, teaching management state recognition and machine learning intervention decision-making methods. The positive significance of this model on students' learning autonomy, stress relief and physiological regulation ability was verified by results comparison and correlation analysis. The research can provide method support for intelligent education management, students 'physical and mental state monitoring and personalized teaching intervention.

2 Related work

The relationship between students' learning pressure and physical and mental regulation has become an important research direction in the intersection field of education management and health monitoring. Moreno et al. confirmed through clinical trials that Hatha yoga and meditation can relieve the academic stress of medical students, indicating that non-drug adjustment methods have a positive effect on students' stress recovery [11]. Starting from college students' online idleness behavior, Nweke et al. pointed out that academic pressure would affect learning behavior performance through fatigue and decreased self-control, suggesting that teaching management should pay attention to the linkage between students' stress, attention and behavioral self-control [12]. Majerova and Sokolova found, based on interviews and diaries, that the happiness of higher education students has a continuous correlation with academic pressure, and the emotional fluctuations and pressure accumulation in students' daily learning experience will affect their learning engagement [13]. Perez-Jorge et al. further analyzed the influence of academic pressure on students' happiness from the context of higher education, and emphasized that educational management should take into account both learning effectiveness and mental health support [14]. These studies provide a theoretical basis for the teaching management of students, but most of them still use questionnaires, interviews and subjective reports as the main data sources, and the objective description of the regulation process of the autonomic nervous system is insufficient.

In terms of physiological signal analysis, heart rate variability has been widely used to evaluate changes in psychological stress. Immanuel et al. summarized that HRV can reflect the changes of psychological stress in healthy adults and is an important index to evaluate the regulation state of the autonomic nervous system [15]. Ishaque et al. summarized the development trend of HRV signal analysis and believed that time domain, frequency domain and nonlinear features could provide effective support for physiological state recognition [16]. With the popularity of wearable sensors, Gedam and Paul sorted out psychological stress detection methods based on wearable devices and machine learning, and pointed out that the fusion of heart rate, galvanic skin and motion data can improve the stability of stress recognition [17]. Albaladejo-Gonzalez et al. compared the performance of different machine learning models in stress detection based on heart rate, and discussed the ability of transfer learning, which provides a reference for student state recognition across scenarios [18]. Gomes et al. reviewed wearable sensors in mental health monitoring, indicating that continuous data collection can enhance the real-time performance of mental state monitoring [19]. Abd Al-Alim et al. further applied machine learning to stress detection in a free-living environment, indicating that real scene data can help to improve the application value of the model [20].

In recent years, HRV feedback and continuous monitoring have been gradually used in the research of attention control and psychological recovery. Blaser et al. found that a single HRV biofeedback may affect attention control, indicating that there is a connection between autonomic nervous regulation and learning attention state [21]. Castro Ribeiro et al. verified the potential effect of HRV biofeedback to alleviate mental health symptoms, which provided physiological feedback basis for the design of teaching intervention [22]. Matyevich et al. investigated the reliability of HRV and pupillary response of college students under autonomic disturbance, suggesting that multi-modal physiological indicators can be used to evaluate students' state [23]. Kane et al. conducted a systematic review of continuous HRV monitoring of doctors and proved that stress and recovery states could be tracked through long-term physiological data [24]. In general, the existing research has covered academic stress, HRV analysis, wearable sensors and machine learning stress detection respectively. However, the research that combines the teaching management process of students with autonomic nervous system regulation indicators, learning behavior data and intelligent recognition models is still limited.

3 Proposed method

3.1 The construction method of multi-source state vector for student-subject teaching management

For the student-subject teaching management scenario, the student status cannot be represented by grades or classroom performance alone, but also needs to include learning behavior, physiological regulation and subject participation. In this paper, the ith student is taken as the basic modeling object, and the platform learning records, classroom interaction records, physiological signals collected by wearable devices and teaching feedback data are mapped into a multi-source state vector, which provides an input basis for subsequent calculation of autonomic nervous system regulation index and recognition of teaching management status.In order to more clearly present the transformation process of multi-source data to comprehensive state vector in the student-subject teaching management scenario, this paper integrates learning platform logs, classroom interaction records, wearable physiological signals and teaching feedback data into the unified processing flow, and completes the fusion expression through the extraction of behavioral features, physiological features and subject participation features. The specific construction path is shown in Figure 1.

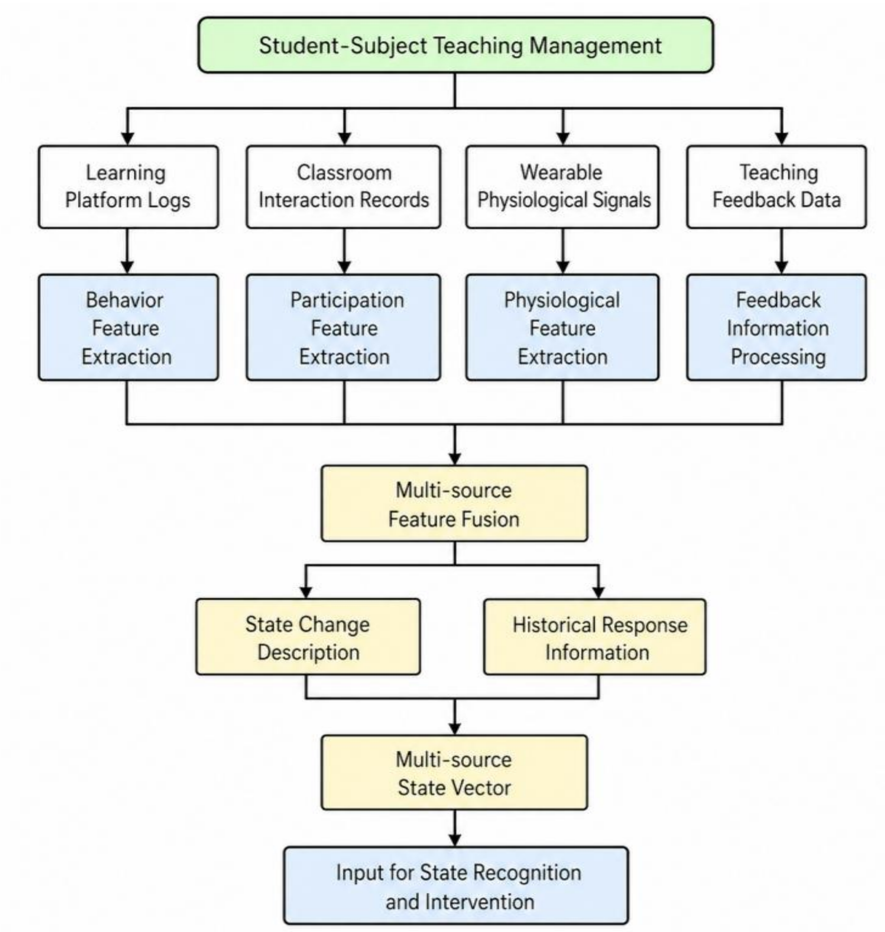

Figure 1: Flow chart of multi-source state vector construction for student subject teaching management

It can be seen from Figure 1 that the state vector under the teaching management of the student subject is not generated by a single academic performance or classroom performance, but is formed by multiple types of information such as learning behavior, classroom interaction, physiological regulation and teaching feedback. This process can transform the originally scattered teaching management data into structured input, so that the subsequent state recognition model not only focuses on students 'explicit learning performance, but also further reflects the changes of their subject participation level and autonomic nervous system regulation.

The intensity of student learning behavior is defined as follows:

$$\mathrm{B_i} = \mathrm{a_1 L_i} + \mathrm{a_2 T_i} + \mathrm{a_3 I_i} + \mathrm{a_4 C_i} \tag{1}$$

where, B_i represents the intensity of the ith student's learning behavior, L_i represents the login frequency of the learning platform, T_i represents the completion rate of learning tasks, I_i represents the frequency of classroom interaction, C_i represents the continuous participation in the classroom, and a_1 to a_4 are the corresponding weights. This index is used to characterize the level of students' explicit learning engagement in the subject teaching management.

The physiological regulation state is characterized as follows:

$$\mathcal{P}_\mathrm{i} = \mathrm{b_1 R_i} + \mathrm{b_2 H_i} - \mathrm{b_3 E_i} - \mathrm{b_4 D_i} \tag{2}$$

In the formula, P_i represents the physiological adjustment state value of students, R_i represents the recovery feature of heart rate variability, H_i represents the high frequency power feature, E_i represents the galvanic skin response intensity, D_i represents the deviation degree of heart rate, and b_1 to b_4 represents the weight of physiological characteristics. This expression places the parasympathetic restorative capacity into the same computational framework as the stress arousal feature.

The participation level of students is defined as follows:

$$\mathcal{M}_\mathrm{i} = \mathrm{c_1 G_i} + \mathrm{c_2 S_i} + \mathrm{c_3 F_i} + \mathrm{c_4 V_i} \tag{3}$$

where, M_i represents the participant's participation level, G_i represents the completion of learning goal setting, Si represents the ability to select learning strategies, F_i represents the quality of feedback response, V_i represents the degree of expression of learning opinions, and c_1 to c_4 represents the weight of the participant's management characteristics. This index is used to reflect students' active participation and self-regulation ability in teaching management.

After the calculation of behavioral, physiological and subject participation features, the multi-source state vector is constructed as follows:

$$\mathbf{Z}_i = [\mathcal{B}_i, \mathcal{P}_i, \mathcal{M}_i, \Delta_i, \Omega_i]^T \tag{4}$$

where Z_i represents the integrated state vector of the ith student, Δ_i represents the magnitude of state change in adjacent learning phases, and Ω_i represents the response results after the history teaching intervention. Through this vector, the teaching management process of the student subject is transformed into structured data that can be calculated, comparable and input to the model, which lays the foundation for subsequent feature normalization, state recognition and intervention decision-making.

3.2 Learning behavior and physiological signal feature normalization calculation method

After the construction of multi-source state vector, there are obvious differences between learning behavior data and physiological signal data in dimension, value range and change direction. For example, higher values of indicators such as learning task completion rate and classroom interaction frequency usually represent more adequate learning engagement, while higher values of indicators such as galvanized skin response intensity and deviation degree of heart rate may mean enhanced stress arousal. In order to avoid the weight shift caused by the direct input of different scale features into the model, the learning behavior and physiological signal features are unified and normalized, so that all kinds of indicators can participate in the subsequent calculation in the same numerical space.

Let the original observation of the RTH sample on the s-th feature be $\chi_{r,s}$, and its direction consistency normalization result is as follows:

$$\hat{\chi}_{r,s} = \begin{cases} \dfrac{\chi_{r,s} - \chi_s^{min}}{\chi_s^{max} - \chi_s^{min} + \varepsilon}, \kappa_s = 1 \\ \dfrac{\chi_s^{max} - \chi_{r,s}}{\chi_s^{max} - \chi_s^{min} + \varepsilon}, \kappa_s = -1 \end{cases} \quad (5)$$

where, $\chi_{r,s}$ represent the normalized feature value after direction consistency, χ_s^{max} and χ_s^{min} represent the maximum and minimum value of the s-th feature in the sample set respectively, ε is a small constant to prevent the denominator from being zero, $\kappa_s=1$ represents the forward index, $\kappa_s=-1$ represents the reverse index. Through this treatment, enhanced learning engagement, decreased stress, and improved regulation ability were uniformly translated into higher feature scores.

Considering that signals such as heart rate and galvanic skin collected by wearable devices may be affected by movement, contact loosening or short-term noise, this paper further introduces robust standardized calculation to reduce the interference of outliers on model input:

$$\bar{\chi}_{r,s} = \frac{\hat{\chi}_{r,s} - \mathrm{Med}(\hat{\chi}_s)}{\mathrm{IQR}(\hat{\chi}_s) + \varepsilon} \quad (6)$$

where, $\bar{\chi}_{r,s}$ represents the feature value after robust normalization, $\mathrm{Med}(\hat{\chi}_s)$ represents the median of the s-th normalized feature, and $\mathrm{IQR}(\hat{\chi}_s)$ represents the interquartile range. Compared with the direct mean normalization, this method has stronger adaptability to short-term abnormal fluctuations in class, and can retain students 'continuous learning state and the changes of autonomic nervous system regulation.

After the single feature processing, this paper constructs a weighted normalized input vector according to the stability of feature collection:

$$Q_r = [\lambda_1\bar{\chi}_{r,1}, \lambda_2\bar{\chi}_{r,2}, \dots, \lambda_m\bar{\chi}_{r,m}]^T \quad (7)$$

where, Q_r represents the normalized input vector of the RTH sample, m represents the total number of features, and λ_s represents the stability weight of the s-th feature. Higher weights were given to features with low missing rate, strong collection continuity and higher correlation with learning state changes. For the features with more noise or obvious short-term fluctuations, the input influence is appropriately reduced. After the above calculation, learning behavior data and physiological signal data were transformed into model inputs with consistent direction, unified scale and stability constraints, which provided a reliable data basis for subsequent calculation of autonomic nervous system regulation index and recognition of teaching management status.

3.3 Calculation method of autonomic nervous system regulation index based on heart rate variability

Heart rate variability (HRV) is an important physiological index to evaluate the regulatory ability of the autonomic nervous system, which can reflect the subtle fluctuations of adjacent heart intervals. The student-centered teaching management model emphasizes students' initiative in learning task selection, classroom feedback and self-regulation, and its positive significance is not only reflected in the improvement of learning behavior, but also in the change of stress recovery ability, attention stability and parasympathetic regulation level. Therefore, based on the interbeat sequence collected by wearable devices, this paper constructs the autonomic nervous system regulation index, which is used to quantify the physiological regulation level of students under different teaching management states.

Let the adjacent interbeat interval sequence of the ith student in the u-th observation window be $\rho_{i,u,q}$. The adjacent RMS features are calculated as follows:

$$\Re_{i,u} = \sqrt{\frac{1}{N_{i,u}-1}\sum_{q=1}^{N_{i,u}-1}\left(\rho_{i,u,q+1}-\rho_{i,u,q}\right)^2} \tag{8}$$

where $\Re_{i,u}$ represents the adjacent RMS features of the ith student in the u-th observation window, $\rho_{i,u,q}$ represents the q-th interbeat interval, and $N_{i,u}$ represents the number of effective interbeats in this window. A higher value of this index usually indicates greater parasympathetic regulation and stress resilience.

In order to describe the overall fluctuation degree of the interbeat interval, the standard deviation characteristics are further calculated:

$$\mathfrak{S}_{i,u} = \sqrt{\frac{1}{N_{i,u}-1}\sum_{q=1}^{N_{i,u}}\left(\rho_{i,u,q}-\bar{\rho}_{i,u}\right)^2} \tag{9}$$

where, $\mathfrak{S}_{i,u}$ represent the standard deviation characteristics of interbeat intervals, and $\bar{\rho}_{i,u}$ represent the mean interbeat interval in the u-th observation window. This index is used to reflect the overall fluctuation ability of the student's autonomic nervous system, and can supplement the problem that the single adjacent difference feature is insufficient to describe the long-term regulation state.

Autonomic nervous system regulation also needs to consider the balance between sympathetic and parasympathetic nerves. In this paper, the ratio of low frequency power to high frequency power is used as the neural balance feature:

$$\Re_{i,u} = \frac{\Phi_{i,u}^{low}}{\Phi_{i,u}^{high}+\zeta} \tag{10}$$

where $\Re_{i,u}$ represents the neural balance ratio, $\Phi_{i,u}^{low}$ represents the low frequency power, $\Phi_{i,u}^{high}$ represents the high frequency power, and ζ is a tiny constant to prevent the denominator from being zero. When the ratio increases, it usually indicates that the stress arousal or sympathetic nerve advantage is enhanced, and it is necessary to combine the teaching scene to further determine whether the students are in a state of tension or fatigue. The indicators of autonomic nervous system regulation characteristics are shown in Table 1.

Table 1: Index table of autonomic nervous system regulation characteristics

Indicator Category	Feature Indicator	Data Source	Reflected Meaning	Model Function
Time-Domain Regulation Indicator	Adjacent Interbeat Interval Difference	Wearable Heart Rate Sensor	Reflects short-term parasympathetic regulation ability	Determines students' stress recovery level
Time-Domain Fluctuation Indicator	Overall Interbeat Interval Fluctuation	Interbeat Interval Sequence	Reflects the overall regulatory elasticity of the autonomic nervous system	Measures physiological state stability
Frequency-Domain Recovery Indicator	High-Frequency Power	Heart Rate Variability Spectrum	Reflects parasympathetic activity intensity	Identifies relaxation and recovery states
Frequency-Domain Balance Indicator	Low-Frequency/ High-Frequency Power Ratio	Heart Rate Variability Spectrum	Reflects the balance between sympathetic and parasympathetic nerves	Determines the degree of stress arousal
Auxiliary Arousal Indicator	Skin Conductance Response Intensity	Skin Conductance Sensor	Reflects emotional tension and physiological arousal	Assists in correcting stress recognition results

It can be seen from Table 1 that the autonomic nervous system regulation cannot only rely on a single heart rate numerical judgment, but should integrate characteristics such as short-term fluctuations, overall stability, frequency domain balance and physiological arousal. This can more accurately reflect the pressure change and adjustment ability of students in the process of main teaching management.

Based on the above features, this paper constructs the autonomic nervous system regulation index:

$$\mathcal{A}_{\mathrm{i,u}} = \eta_1\widetilde{\mathfrak{R}}_{\mathrm{i,u}} + \eta_2\widetilde{\mathfrak{S}}_{\mathrm{i,u}} + \eta_3\widetilde{\Phi}_{\mathrm{i,u}}^{\mathrm{high}} - \eta_4\widetilde{\mathfrak{R}}_{\mathrm{i,u}} - \eta_5\widetilde{\Theta}_{\mathrm{i,u}} \quad (11)$$

where, $\mathcal{A}_{\mathrm{i,u}}$ represent the autonomic nervous system regulation index, $\widetilde{\mathfrak{R}}_{i,u}, \widetilde{\mathfrak{S}}_{i,u}, \widetilde{\Phi}_{i,u}^{high}, \widetilde{\mathfrak{K}}_{i,u}$ represent the normalized adjacent root mean square difference feature, standard deviation feature, high-frequency power feature and neural balance ratio respectively, Θ~i,u represent the normalized galvanic skin response intensity, and η_1 to η_5 are the feature contribution weights. The higher the index, the better autonomic nervous regulation ability of students in the current teaching management state; A low index indicates that students may have problems such as accumulation of stress, fluctuations in attention, or insufficient recovery. Through this calculation method, the influence of teaching management of students can be extended from the behavior level to the physiological regulation level, which provides a quantitative basis for subsequent state identification and teaching intervention.

3.4 Construction of identification model of teaching management state of student subject

After completing the construction of multi-source state vector, feature normalization and calculation of autonomic nervous system regulation index, it is necessary to further map the comprehensive performance of students in the teaching management process into identifiable state categories. Therefore, this paper constructs a teaching management state recognition model for students, which fuses learning behavior features, autonomous participation features and autonomic nervous system regulation features, and outputs the corresponding management state labels. The model identification results are used to support subsequent teaching intervention decisions, so that teaching management changes from experience judgment to data-driven judgment.

Let the normalized behavioral feature vector of the ν-th observation sample be Q_ν, and its corresponding autonomic nervous system regulation index be A_ν. Then the fusion input vector is defined as follows.

$$F_\nu = [Q_\nu^T, \mathcal{A}_\nu]^T \tag{12}$$

where, F_ν represents the integrated input vector of the state recognition model. The vector not only retains the learning behavior information, but also introduces physiological regulation information, which can reflect the real state of students in the main teaching management environment more completely.

In order to extract deep state representation, nonlinear mapping is used to obtain implicit feature representation:

$$H_\nu = \varphi\left(W^{[1]}F_\nu + b^{[1]}\right) \tag{13}$$

where H_ν represents the feature vector of the hidden layer, $W^{[1]}$ represents the weight matrix from the input layer to the hidden layer, $b^{[1]}$ represents the bias term, and $\varphi(\cdot)$ represents the activation function. This process is used to mine the nonlinear association between behavioral variables and physiological variables and improve the adaptability of state recognition to complex learning scenarios.

Let the total number of output state categories of the model be C, and the posterior probability of the state of class c be calculated as follows:

$$\pi_{\nu,c} = \frac{\exp\left(w_c^{[2]T}H_\nu + b_c^{[2]}\right)}{\sum_{g=1}^{C}\exp\left(w_g^{[2]T}H_\nu + b_g^{[2]}\right)} \tag{14}$$

where $\pi^{\nu,c}$ represents the probability that the ν-th sample belongs to the state of class c, $w_c^{[2]}$ and $b_c^{[2]}$ represent the weight vector and bias term of the corresponding class in the output layer, respectively. In this paper, the state of students is divided into four categories: autonomous stable state, participation enhanced state, pressure fluctuation state and regulation risk state, in order to provide a basis for different teaching management strategies.

The final state determination result is expressed as follows:

$$\widehat{\psi}_\nu = \arg\max_{c\in\{1,2,\ldots,C\}} \pi_{\nu,c} \tag{15}$$

where $\widehat{\psi}_\nu$ denotes the predicted state label of the ν-th sample. The results can be directly used as the input of the teaching management system to trigger reminders, feedback, task adjustment and support strategy push. Figure 2 shows the structure of the identification model of the teaching management status of the student subject.

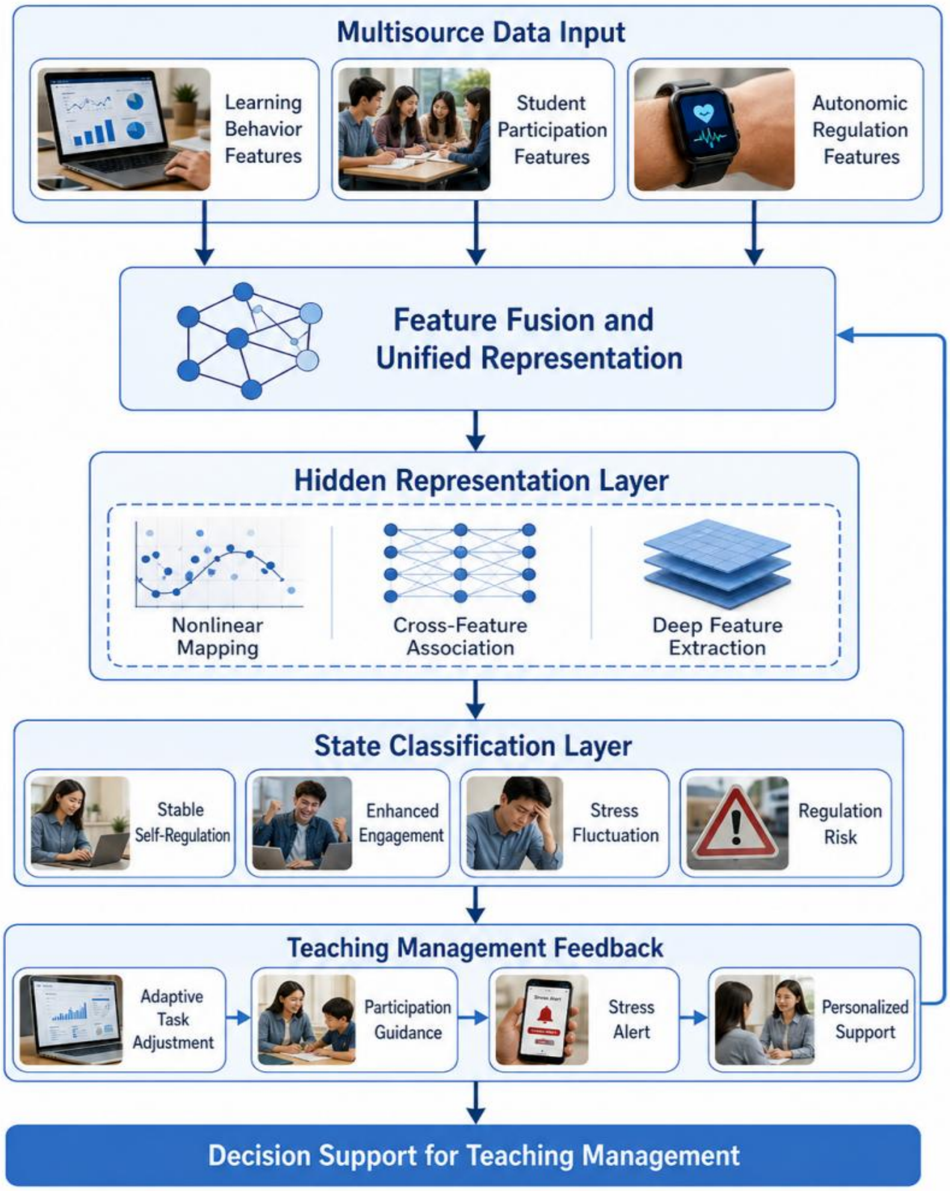

Figure 2: Structure diagram of identification model of teaching management status of student subject

As can be seen from Figure 2, the model is composed of "multi-source input layer -- feature fusion layer -- hidden representation layer -- state classification layer -- management feedback layer". Among them, the multi-source input layer receives learning behavior features, subject participation features and autonomic nervous regulation features. The feature fusion layer completes data splicing and unified expression. The hidden representation layer extracts deep correlation features. The state classification layer outputs four kinds of state probabilities. The management feedback layer transmits the identification results to the subsequent intervention decision module. Through this model, the behavioral changes and physiological changes in the process of teaching management of students can be uniformly identified, which provides a reliable basis for subsequent personalized intervention.

3.5 Teaching management intervention decision-making method integrated with machine learning

After completing the identification of the teaching management status of the student subject, the system needs to generate executable teaching management intervention strategies according to the identification results. In this paper, the intervention decision is regarded as a multi-objective matching problem, and the current status of students, the change of adjustment index, the participant's participation level and the cost of strategy implementation are comprehensively considered. The state probability output from machine learning is used to adaptively adjust the intervention intensity. The intervention strategy is not based on unified reminder, but according to the differences of students in autonomous stability, participation enhancement, pressure fluctuation and adjustment risk, the management measures such as task adjustment, participation guidance, stress early warning and personalized support are matched respectively.

Let the combined utility of the ν-th observation sample corresponding to the ℓ -th intervention strategy be as follows:

$$\mathcal{U}_{\nu,\ell} = \mu_1 \Pi_{\nu,\ell} + \mu_2 \Lambda_{\nu,\ell} + \mu_3 \Gamma_{\nu,\ell} - \mu_4 \Xi_{\nu,\ell} \tag{16}$$

where, $\mathcal{U}_{\nu,\ell}$ represent the intervention strategy utility value, $\Pi_{\nu,\ell}$ represent the matching degree between the state and the strategy, $\Lambda_{\nu,\ell}$ represent the student subject participating in the improvement expectation, $\Gamma_{\nu,\ell}$ represent the autonomic nervous system regulating the improvement expectation, $\Xi_{\nu,\ell}$ represent the strategy execution load, μ_1 to μ_4 are the utility weights. The formula takes the benefits of teaching management and implementation costs into account at the same time, avoiding that the intervention strategy only pursues the intensity and ignores the ability of students to bear.

The optimal intervention strategy is chosen as follows:

$$\ell_\nu^* = \arg\max_{\ell \in \mathcal{Y}} \ \mathcal{U}_{\nu,\ell} \tag{17}$$

where, ℓ_ν^* represents the optimal intervention strategy number corresponding to the ν-th observation sample, and Y represents the set of candidate teaching management intervention strategies. Through this calculation, the system is able to select the most suitable management action for the current student state from multiple policies.

In order to ensure that the intervention decision can be continuously updated with the change of students 'status, this paper introduces the feedback effect evaluation mechanism:

$$\mathcal{E}_\nu^{(t+1)} = \tau \mathcal{E}_\nu^{(t)} + (1-\tau)\left[\left(\mathcal{A}_\nu^{after} - \mathcal{A}_\nu^{before}\right) + \upsilon\left(\mathcal{O}_\nu^{after} - \mathcal{O}_\nu^{before}\right)\right] \tag{18}$$

where, $\mathcal{E}_\nu^{(t+1)}$ represents the updated intervention feedback effect, $\mathcal{E}_\nu^{(t)}$ represents the previous round feedback effect, τ represents the historical feedback retention coefficient, $\mathcal{A}_\nu^{\text{before}}$ and $\mathcal{A}_\nu^{\text{after}}$ represent the autonomic nervous system regulation index before and after the intervention, respectively. $\mathcal{O}_\nu^{\text{before}}$ and $\mathcal{O}_\nu^{\text{after}}$ represent the level of learning autonomy before and after the intervention, respectively, and υ represents the moderating coefficient of the change in learning autonomy. This formula can reflect the improvement of physiological regulation and the improvement of learning subjectivity at the same time, which makes the intervention evaluation more suitable for the research theme of this paper.

According to the feedback results, the subsequent recommendation tendencies of different intervention strategies were revised:

$$\mathfrak{I}_{\ell}^{(t+1)} = \mathfrak{I}_{\ell}^{(t)} + \alpha_{\mathrm{fb}} \left(\mathcal{E}_{\nu}^{(t+1)} - \overline{\mathcal{E}}_{\ell}^{(t)} \right) \tag{19}$$

where, $\mathfrak{I}_{\ell}^{(t+1)}$ represents the recommendation tendency of the intervention strategy of the ℓ class after updating, $\mathfrak{I}_{\ell}^{(t)}$ represents the recommendation tendency of the last round, α_{fb} represents the feedback learning rate, and $\overline{\mathcal{E}}_{\ell}^{(t)}$ represents the average feedback effect of this type of strategy in historical samples. This update method can make the intervention strategies with better effects obtain higher recommendation weights in similar states, thus forming a closed loop of continuous optimization of teaching management.

Through the above decision-making method, the teaching management system can dynamically generate intervention strategies according to the changes in the participation performance of the students and the regulation of the autonomic nervous system. Compared with the immobilized management method, this method can adjust the teaching support path in time when students 'pressure increases, participation declines or adjustment risks appear, so that the student-subject teaching management mode has the technical basis of calculable, feed-back and sustainable optimization.

4 Results and discussion

In order to verify the positive significance of the student-subject teaching management model on the regulation of students 'autonomic nervous system, this paper selected 120 undergraduates from a university as experimental objects, including 58 male students and 62 female students, aged 18-23 years. All students are from the same semester of public courses and professional basic courses, with a relatively consistent learning cycle and classroom management environment. The experiment period was set to 8 weeks, and the first 2 weeks were used as the baseline observation stage, and the conventional teaching management method was used to collect the data of students 'learning behavior and physiological state. In the last 6 weeks, the student-centered teaching management model was implemented to guide students to participate in learning goal setting, task rhythm adjustment, classroom feedback expression and self-learning evaluation. The data collection content included the login frequency of the teaching platform, the completion rate of learning tasks, the number of classroom interactions, feedback submission, the score of the learning autonomy scale, and the physiological indicators such as heart rate, heart rate variability, galvanic skin response and resting recovery state recorded by wearable devices.

In the process of data processing, the samples with abnormal device wearing, serious heart interval missing and incomplete classroom records were deleted. Finally, 112 effective student samples were retained, and 16800 effective learning behavior records, 13440 physiological signal fragments and 2860 teaching feedback records were formed. In order to ensure the stability of model training and validation, this paper divides the training set, validation set and test set according to the ratio of 7:2:1, and normalizes the characteristics of learning behavior and physiological signal. The evaluation indicators mainly include learning autonomy score, autonomic nervous system regulation index, stress level, state recognition accuracy, Precision, Recall and F1 score. The subsequent experiments analyzed the effectiveness of the proposed method from the aspects of students 'autonomy change, the improvement of physiological regulation indicators, the difference of stress level, the correlation between behavior and physiology, and the recognition performance of machine learning.

4.1 Analysis of students' learning autonomy change

Students' learning autonomy is an important index to evaluate the implementation effect of the student-centered teaching management model. This paper evaluates students' learning autonomy from five dimensions of learning goal setting, task active completion, classroom participation initiative, self-feedback ability and learning plan execution, and compares and analyzes the results before and after implementation. Figure 3 shows the comparison between before and after each dimension of student learning autonomy.

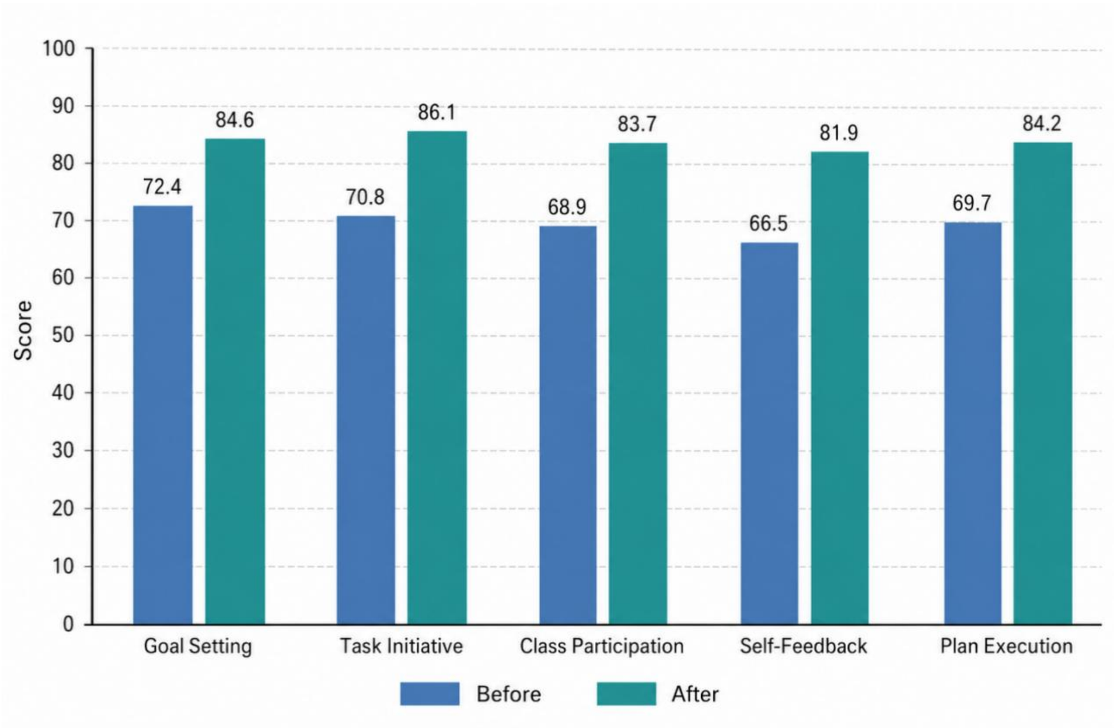

Figure 3: Bar chart of comparison before and after each dimension of student learning autonomy

It can be seen from Figure 3 that after the implementation of the student-centered teaching management mode, the learning autonomy of all dimensions shows an increasing trend. The score of learning goal setting increased from 72.4 points to 84.6 points, an increase of 12.2 points. The score of active task completion increased from 70.8 to 86.1, an increase of 15.3; The score of classroom participation initiative increased from 68.9 to 83.7, an increase of 14.8; The self-feedback ability increased from 66.5 to 81.9, an increase of 15.4 points; The learning plan implementation score increased from 69.7 to 84.2, an increase of 14.5 points. The results show that the student-subject teaching management model can enhance students 'sense of participation and control in the learning process, make them gradually shift from passive task completion to active planning, active feedback and active adjustment, and provide a behavioral basis for the subsequent improvement of autonomic nervous system regulation.

4.2 Analysis of changes in regulation indexes of autonomic nervous system

Autonomic nervous system regulation index can reflect students' stress recovery ability and physiological stability in the process of teaching management. In this paper, RMSSD, SDNN, HF and LF/HF are selected as core indicators to analyze the change trend of different stages before and after the implementation of the student-subject teaching management model. RMSSD and HF mainly reflect the ability of parasympathetic regulation, SDNN reflects the level of overall heart rate variation, and LF/HF is used to observe the balance state of sympathetic and parasympathetic nerves. The changes of core indicators of autonomic nervous system regulation are shown in Figure 4.

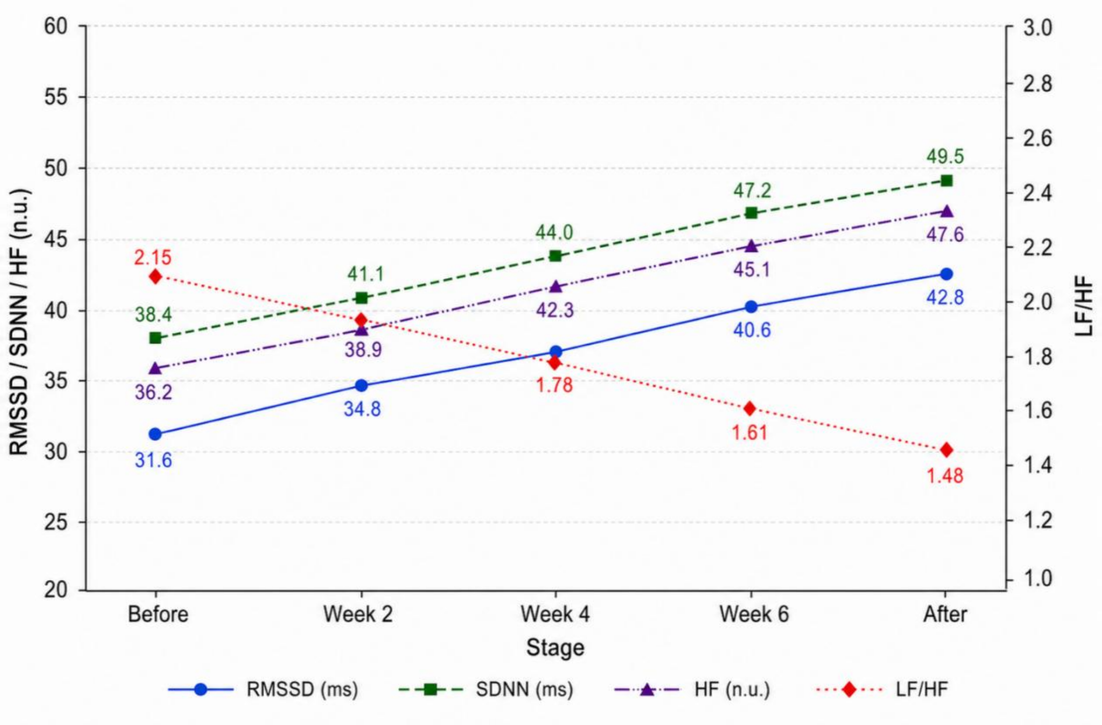

Figure 4: Line chart of changes in core indicators of autonomic nervous system regulation

As can be seen from Figure 4, with the continuous implementation of the student-centered teaching management mode, RMSSD is increased from 31.6ms to 42.8ms, SDNN is increased from 38.4ms to 49.5ms, and HF is increased from 36.2n.u. It was elevated to 47.6 n.u., indicating that the parasympathetic nerve activity and physiological recovery ability of students were gradually enhanced. At the same time, LF/HF decreased from 2.15 to 1.48, indicating that the stress arousal level of students decreased and the autonomic nervous system tended to be more balanced. The results show that the student-subject teaching management model not only improves the learning autonomy, but also has a positive impact on students 'physiological regulation state.

4.3 Comparison of students' stress levels under different teaching management models

In order to further test the regulating effect of the student-centered teaching management model on students 'physical and mental load, this paper compared and analyzed the stress levels under the student-centered teaching management model, the traditional teacher-led teaching management model and the general mixed teaching management model. The stress level was calculated by heart rate variability index, galvanic skin response intensity and subjective stress score. The higher the value, the more obvious the stress load of students. Figure 5 shows the distribution of students' stress levels under different teaching management modes.

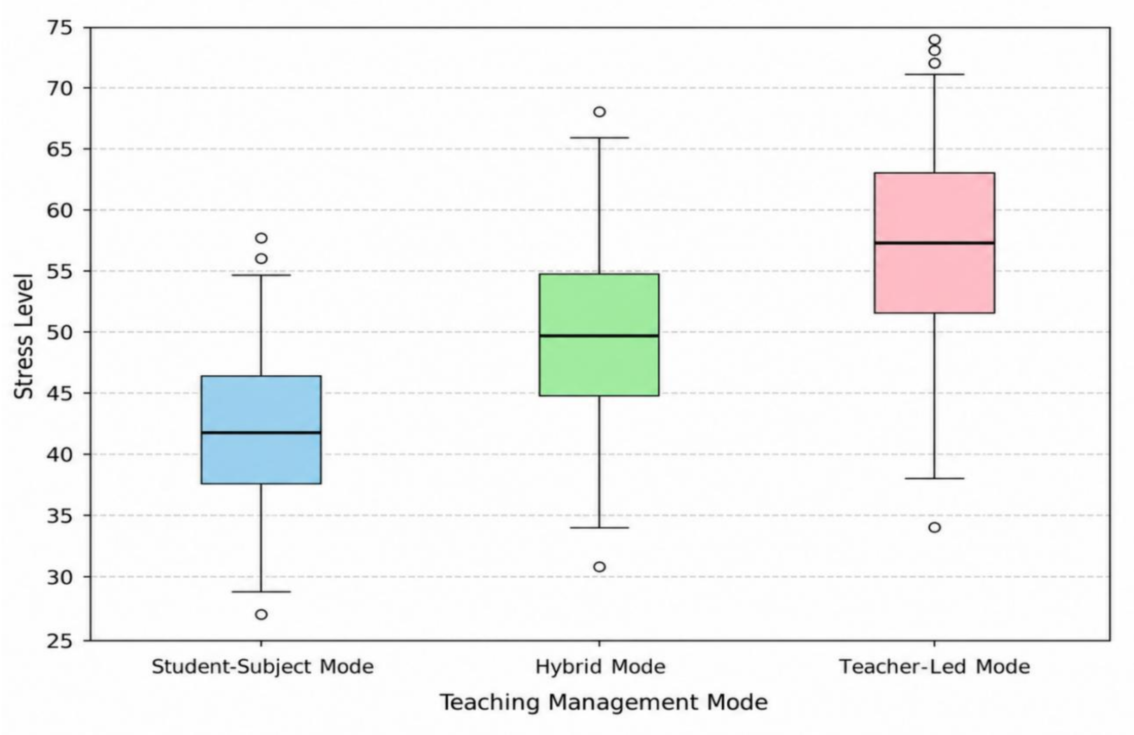

Figure 5: Box plots of stress level distribution under different teaching management modes

As can be seen from Figure 5, the overall stress level under the student-centered teaching management mode is the lowest, with a median of 41.8 and a interquartile range of 8.6. The median pressure of blended teaching management mode was 49.7, and the interquartile range was 10.3; The pressure level of the traditional teacher-dominated teaching management mode was the highest, with a median of 57.4, a interquartile range of 11.8, and more discrete points with high values. Compared with the traditional model, the median pressure of students in the student-centered teaching management model decreased by 15.6, and the decrease was about 27.2%. Compared with the hybrid mode, the decline is 7.9, or about 15.9%. The results show that the student-subject teaching management model can effectively alleviate students 'learning pressure, and show better stability in reducing the fluctuation range of group pressure.

4.4 Correlation analysis of learning behavior characteristics and physiological regulation ability

In order to further analyze the relationship between students 'learning behavior and physiological regulation ability, this paper selected learning participation as a comprehensive behavior index, which was calculated by combining platform login activity, task active completion rate, classroom interaction frequency and feedback submission. The autonomic nervous system regulation index was calculated based on the characteristics of heart rate variability. Figure 6 shows the regression relationship between learning engagement and autonomic nervous system regulation index.

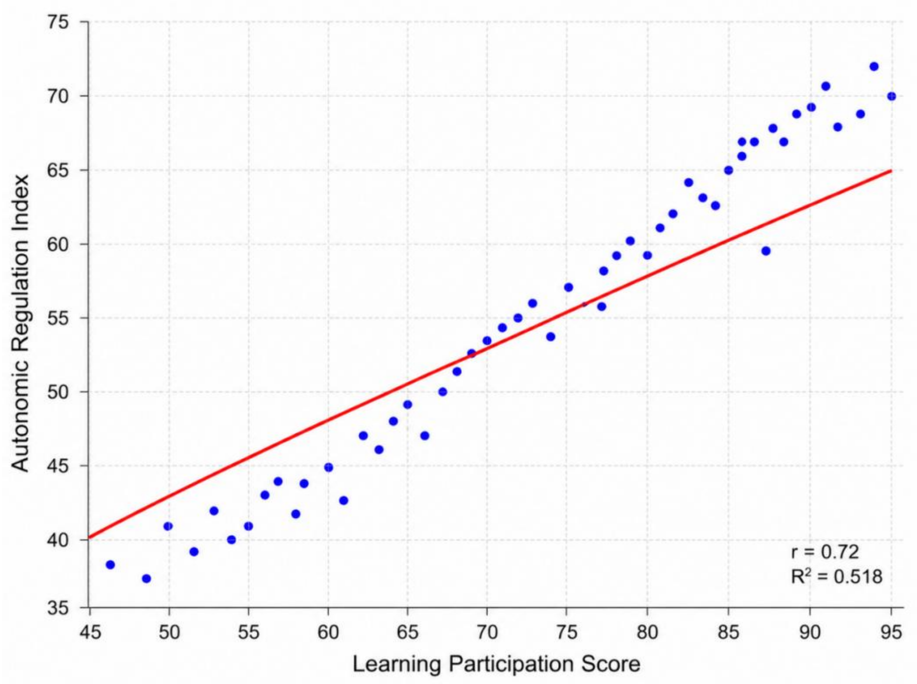

Figure 6: Regression diagram between learning engagement and autonomic nervous system regulation index

As can be seen from Figure 6, there is a significant positive correlation between students 'learning engagement and autonomic nervous system regulation index, and the scatter points are distributed along the regression line, indicating that with the improvement of learning engagement, students 'autonomic nervous system regulation ability is enhanced synchronously. The results of regression analysis showed that the correlation coefficient r was 0.72 and the determination coefficient R^2 was 0.518, indicating that learning engagement could explain about 51.8% of the variation of autonomic nervous system regulation index. The regression slope was 0.63, indicating that an increase of 10 units in learning engagement resulted in an average increase of 6.3 units in the autonomic nervous system regulation index. Further observation found that when learning engagement was less than 60 points, students 'adjustment index was mostly distributed below 45. When the learning participation was increased to more than 80 points, the adjustment index was mainly concentrated between 58 and 72. The results showed that the student-subject teaching management model not only improved the explicit learning behavior, but also promoted the stress recovery and physiological adjustment ability of students by improving the level of students 'learning participation, and there was a relatively stable synergistic change relationship between the two.

4.5 Recognition performance of machine learning model and effectiveness verification of teaching intervention

In order to verify the state recognition ability and the application value of teaching intervention of the proposed method in the student-subject teaching management scenario, SVM, Random Forest, XGBoost, MLP and the model of this paper are selected for comparative analysis, and the actual effect of teaching management strategy is evaluated by combining the change of the proportion of students 'state before and after the intervention. Figure 7 shows the ROC curves of state recognition for different machine learning models.

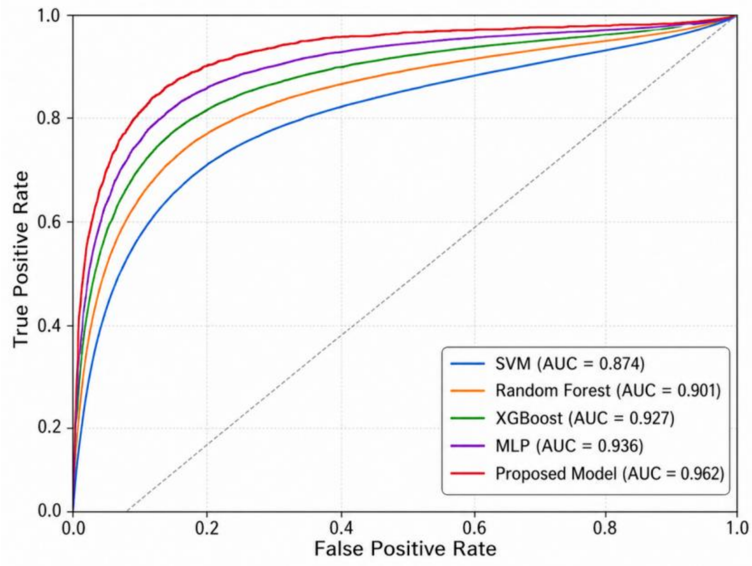

Figure 7: ROC curves for state recognition of different machine learning models

Figure 7 shows that each model has a certain ability to identify student states, but the overall performance of the proposed model is the best, and its ROC curve is outside the other models, and the AUC value reaches 0.962. It is higher than 0.936 of MLP, 0.927 of XGBoost, 0.901 of Random Forest and 0.874 of SVM. Further combined with the analysis of the test set results, the Accuracy, Precision, Recall and F1 value of the proposed model reach 94.8%, 93.9%, 94.3% and 94.1%, respectively. It shows that the constructed multi-source state modeling and physiological regulation feature fusion method can more accurately distinguish the autonomous stable state, participation enhancement state, pressure fluctuation state and regulation risk state. The results show that the joint modeling of learning behavior features and autonomic nervous system regulation features can significantly improve the stability and discrimination ability of teaching management state recognition.

Based on the model identification results, this paper further analyzes the changes in the structure of student states before and after the implementation of the intervention. The changes in the proportion of student states before and after the teaching intervention are shown in Figure 8.

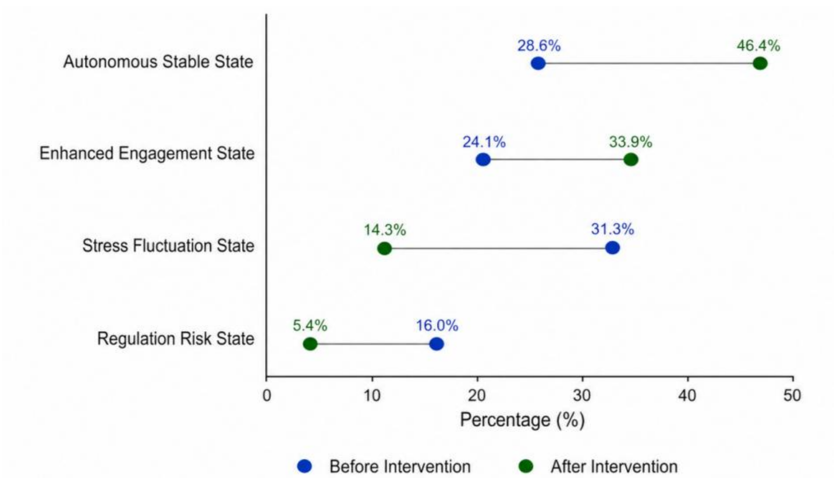

Figure 8: Dumbbell plot of changes in the proportion of student states before and after the teaching intervention

It can be seen from Figure 8 that the proportion of positive states increased significantly and the proportion of negative states decreased significantly after the implementation of the intervention. Among them, the autonomous stable state increased from 28.6% to 46.4%, an increase of 17.8 percentage points; Participation enhancement status increased from 24.1% to 33.9%, an increase of 9.8 percentage points. At the same time, the pressure fluctuation state decreased from 31.3% to 14.3%, down 17.0 percentage points; Adjusted risk status decreased from 16.0% to 5.4%, a decrease of 10.6 percentage points. The results showed that after the implementation of hierarchical teaching management intervention based on the recognition results of machine learning, students could quickly transfer from the state of pressure fluctuation and adjustment risk to the state of independent stability and participation enhancement.

4.6 Discussion

It can be seen from the experimental results that the student-subject teaching management mode has a relatively stable positive impact on students 'learning behavior and autonomic nervous system regulation. Compared with the traditional teacher-led model, this model enabled students to obtain a higher sense of participation and control in the process of teaching management through the co-construction of learning objectives, autonomous adjustment of task rhythm, classroom feedback expression and personalized support mechanism. 4.1 The results showed that students significantly improved in the dimensions of goal setting, active task completion, classroom participation, self-feedback and plan implementation. Among them, the self-feedback ability was increased by 15.4 points, and the active task completion was increased by 15.3 points, indicating that the strengthening of students 'subjective status could directly improve their explicit learning behavior. The improvement of learning behavior provided the basis for the subsequent changes in physiological regulation. Students were no longer in the state of passive acceptance and external urging for a long time in learning tasks, and their mental load and sense of uncertainty were reduced.

The changes of autonomic nervous system regulation indicators further showed that the value of this teaching management model was not limited to the improvement of learning performance, but also reflected in the improvement of students 'stress recovery and physiological stability. RMSSD is improved from 31.6 ms to 42.8 ms, SDNN is improved from 38.4 ms to 49.5 ms, HF is improved from 36.2 n.u. Increased to 47.6 n.u., indicating enhanced parasympathetic activity and overall heart rate variability. At the same time, LF/HF decreased from 2.15 to 1.48, indicating that the excessive sympathetic arousal was relieved, and the tension state of students in the learning process was reduced. This result is mutually confirmed with the pressure level distribution change in 4.3. The median pressure under the student-dominated teaching management mode is 41.8, which is significantly lower than that of the traditional teacher-dominated mode (57.4), and the degree of box dispersion is smaller, indicating that this mode not only reduces the average pressure level, but also reduces the pressure fluctuation among students.

From the perspective of the relationship between behavior and physiology, learning participation was positively correlated with autonomic nervous system regulation index, the correlation coefficient reached 0.72, and the determination coefficient was 0.518, indicating that learning participation behavior could explain more than half of the changes in physiological regulation index. This result suggested that student-subject teaching management did not simply change the way of classroom organization, but formed a linkage relationship between learning behavior, emotional experience and physiological regulation. When students can take the initiative to set goals, adjust the pace of tasks and get feedback in time, the sense of stress in the learning process is easier to be recognized and released, and the physiological regulation system is easier to maintain a balanced state.

The recognition results of the machine learning model further enhance the application feasibility of the model. The AUC of the proposed model reaches 0.962, and the Accuracy, Precision, Recall and F1 value reach 94.8%, 93.9%, 94.3% and 94.1%, respectively, which are better than those of SVM, Random Forest, XGBoost and MLP. It shows that the fusion of multi-source learning behavior features and autonomic nervous regulation features can more accurately distinguish students 'learning management status. The change of the proportion of states before and after the intervention also showed that the autonomous stable state increased from 28.6% to 46.4%, and the adjusted risk state decreased from 16.0% to 5.4%, which proved that the model identification results could effectively serve the decision-making of teaching intervention.

In general, the positive significance of the student-subject teaching management model is reflected in three levels: improving students 'learning autonomy at the behavioral level, promoting the balance of the autonomic nervous system at the physiological level, and realizing state recognition and intervention feedback through machine learning models at the technical level. This model provided a feasible path for teaching management from experience-based judgment to data-driven support, and also provided a new method reference for the monitoring and personalized management of students 'physical and mental states in education scenarios.

4.7 Limitations

Although this paper verifies the positive significance of the student-subject teaching management model from three levels of learning behavior, physiological signals and machine learning recognition, there are still some limitations in the research. In terms of sample sources, the experimental subjects mainly come from undergraduates of the same university, the course types focus on public courses and professional basic courses, and the age of students, learning environment and teaching system are relatively close. Such a sample setting is beneficial to control the interference factors of the experiment, but it also limits the promotion of the conclusions in different schools, different student segments and different professional courses. Follow-up studies also need to expand the sample size to include vocational colleges, graduate programs, and student groups with different levels of learning stress to examine the applicability of the model in more complex educational scenarios.

In terms of data acquisition, although this paper introduces physiological indicators such as heart rate, heart rate variability and galvanization of skin response, the data of wearable devices are easily affected by changes in wearing tightness, physical activity, environmental temperature and classroom behavior. Some short-term physiological fluctuations are not necessarily caused by the teaching management style, but may also be related to sleep, diet, exercise and personal emotional state. In this paper, the influence of noise is reduced by abnormal segment elimination and feature normalization, but it is still difficult to completely eliminate the interference of individual life factors on the regulation index of the autonomic nervous system. Therefore, variables such as sleep quality, exercise intensity, pre-class emotional state, and long-term health habits can be combined in the follow-up to improve the accuracy of physiological data interpretation.

In terms of model construction, the state recognition model proposed in this paper mainly focuses on the characteristics of learning behavior and the regulation characteristics of the autonomic nervous system, which can identify the basic states of students in the process of classroom management, but the description of deep psychological factors is still insufficient. For example, variables such as learning motivation, achievement anxiety, peer relationships, and perceived teacher support may also affect student stress levels and physiological regulation states. If we only rely on behavior logs and physiological signals, we may not be able to fully explain the psychological mechanism behind students 'state changes. Subsequent research can introduce text feedback analysis, classroom speech emotion recognition and psychological scale data to construct a richer multimodal student state recognition framework.

In terms of experimental period, this paper set up an 8-week observation and intervention process, which could reflect the influence of short-term teaching management mode changes on students 'learning autonomy and physiological regulation state, but the verification of long-term stable effects was still insufficient. Whether the student-subject teaching management model can continuously improve the autonomic nervous system regulation ability in a semester, an academic year or even a longer period needs to be further tracked. Follow-up studies can adopt longitudinal experimental design to observe whether there are continuous changes in students 'state transition, stress resilience and learning autonomy, so as to more comprehensively evaluate the long-term application value of this model.

5 Conclusion

Focusing on the positive significance of the student-subject teaching management mode for the regulation of autonomic nervous system, this paper combines the educational management process, physiological signal analysis and machine learning modeling, and constructs a technical framework for the identification of students 'learning states and the decision-making of teaching intervention. Through learning behavior data, classroom participation data, heart rate variability, galvanized skin response and teaching feedback information, the multi-source state vector was formed, and on this basis, the feature normalization, autonomic nervous system regulation index calculation, student management state recognition and intervention strategy matching were completed, so that the teaching management process could turn from experience judgment to data-driven analysis. The experimental results show that after the implementation of the student-oriented teaching management model, the dimensions of learning goal setting, task active completion, classroom participation, self-feedback and plan execution are improved, and the self-feedback ability is increased by 15.4 points, and the task active completion is increased by 15.3 points, indicating that students 'initiative and self-management ability in the learning process are significantly enhanced. In terms of physiological regulation, RMSSD increased from 31.6 ms to 42.8 ms, SDNN increased from 38.4 ms to 49.5 ms, and HF increased from 36.2 n.u. LF/HF decreased from 2.15 to 1.48, indicating that the students' parasympathetic regulation ability was enhanced and the level of stress arousal was reduced. Machine learning verification results show that the AUC of the proposed model reaches 0.962, and the Accuracy, Precision, Recall and F1 value reach 94.8%, 93.9%, 94.3%and 94.1%respectively, which are better than SVM, Random Forest, XGBoost and MLP models. After the intervention, the autonomous stable state increased from 28.6% to 46.4%, and the regulated risk state decreased from 16.0% to 5.4%. In conclusion, the student-subject teaching management model can promote the improvement of learning behavior, physiological stress recovery and intelligent intervention optimization. The research results can provide reference for students 'status perception, teaching management decision-making and physical and mental health support in educational scenarios.

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