# Mental Health Monitoring and Abnormality Analysis for Sports Majors Based on Dynamic Threshold

**Fang Liu[1]***

**Abstract**

The mental health monitoring and abnormality analysis lay the basis for effective stress regulation of sports majors and help them resist mental illness and improve learning efficiency. This paper conducts mental health monitoring and abnormality analysis for sports majors based on a dynamic threshold. Firstly, the authors explained the flow of the dynamic mental health monitoring for sports majors and provided the prediction flow of the proposed model. Then, based on the Gradient Boosting Decision Tree (GBDT) model, the mental health level of primary sports college students was predicted. The research steps were detailed, including data preparation and preprocessing, model training, and prediction error calculation, and the dynamic threshold method with the sliding window was described. The non-parametric dynamic threshold setting was adopted to detect the local abnormality in the evaluation data series of the mental health level for sports majors before introducing the structure and principle of the proposed prediction model. The experimental results validate our strategy for mental health monitoring and abnormality analysis of sports majors. The results of relevant research have essential theoretical and practical significance for the works of the mental health of primary sports students.

**Keywords:** dynamic threshold; sports majors; mental health monitoring; abnormal analysis

## 1. Introduction

The characteristics of sports majors change with time and specialization, necessitating special consideration for their mental health (Mitchell, Holtz, & McCarroll, 2022; Vella et al., 2023; Wang & Ma, 2022; Yousef et al., 2022; Zheng, 2022). Sports majors are susceptible to negative emotions such as lack of confidence, depression, and anxiety because they face numerous complex problems, such as the pressure of learning a theoretical and technical course, the learning barriers of cultural knowledge, poor academic performance, physical needs, and employment difficulties (Bork & Mondisa, 2022; Chen & Jiang, 2019; Dong, 2019; Gao, 2022; Hussna et al., 2021; Saadoon, Muhlis, & Mohammed, 2022; Wang, 2020, 2022; Zhao, 2021). Under numerous circumstances, sports majors require immediate physical, psychological, and behavioral supervision and support (Hou, 2022; Di Li, 2022; Li & Wu, 2022; Li & Yu, 2021). With the advancement of information technology, software engineering-based mental health assessment and management approaches have supplanted traditional mental assessment methods and now dominate the creation of developing applications of mental evaluation. The mental health monitoring and anomaly analysis serve as the foundation for effective stress regulation of sports majors, enabling them to resist mental sickness and improve their learning efficiency (Danowitz et al., 2018; Hu, Xi, & Zhang, 2021; Mantzios, Cook, & Egan, 2019; Wiljer et al., 2017; Williams & Washington, 2018).

To establish world-class higher education, it is essential to emphasize college students' mental health education (Wu & Zhang, 2023), optimizing their psychological quality and enhancing their mental health. Liu (2022) collected and sorted dimensional facts twice, performed descriptive analysis, an unbiased t-test, a chi-square test, a variance analysis, and a Student-Newman-Keuls (SNK)-q test on valid data to evaluate the variation of mental health level of students with negative psychological symptoms over two years and to determine the effects of the variation. Widespread use of machine learning techniques for modeling and analyzing sensitive elements. Using a mental health diagnostic system, college students would have an easier time adapting to computer communication. The technology can enhance privacy protection and more accurately reflect the psychological state of college students. Peng Li (2022) designed a hierarchical system consisting of a user layer, a business logic layer, a data access layer, and a data storage layer, drawing on Android's research and the fundamental concept of software engineering, to meet the needs of mental health testing for college students in the era of mobile information. The system under consideration is easy to develop and maintain. Mao and Liu (2022) studied the mental health status of college students using a chaotic algorithm and explored the applicability of a computer monitoring algorithm to the actual psychology of college students. Different mental health analysis models were utilized to match kids with high precision. In addition,

[1] Department of Student Work and Social Sciences, Shijiazhuang University of Applied Technology, Shijiazhuang 050081, China. Email: 2010110597@sjzpt.edu.cn

a model was developed and analyzed following various students' personality characteristics and psychological changes. In the context of big data, Fu (2022) focused primarily on identifying the influencing elements and changing trends of college students' mental health. In the network-oriented scenario, missing values were filled in, and the data series prediction method was used. Lastly, the matching data samples were imported into the enhanced big data dynamic model, and the technique's prediction outcomes on the augmented data were explored in depth. Based on system mechanics, Xun (2021) developed an early warning system for college students' mental health. After gaining an in-depth understanding of the fundamental system mechanics-related theoretical knowledge, a mental health early warning system for college students was built and submitted to rigorous testing.

The dynamic monitoring of mental health has made remarkable strides in recent years. The Internet-based system for remote mental health evaluation and consulting becomes the primary focus of the study. The system's intended audience is now college students, law enforcement officers, and corporation personnel, as opposed to the general public. Existing theories and methods of machine learning and deep learning serve as important references for this paper. However, most existing classical models require the data features to meet preconditions and assumptions strictly, and their application to the massive data volume of remote mental health evaluation and consultation for college students is flawed. Existing research results serve as valuable references for this work. There is currently no research on the mental health monitoring and anomaly analysis of sports majors, a special population. There are numerous parametric and non-parametric approaches for identifying anomalous values. Non-parametric procedures do not require any assumptions on the distribution of variables, in contrast to parametric methods. There are, however, variations between the defined threshold and actual scenarios in real-world applications involving random data and assumptions that are difficult to meet. This work performs mental health monitoring and anomaly analysis for sports majors based on the dynamic threshold to fill a gap. The course of dynamic mental health monitoring for sports majors is described in Section 2. The third section describes the prediction flow of the proposed model and the research stages, including data preparation and preprocessing, model training, and assessment of prediction error. Section 4 adopts the non-parametric dynamic threshold setting to detect the local abnormality in the assessment data series of the mental health level for sports majors and defines the proposed prediction model's structure and the underlying concept. In combination with the experiment, the output errors of several models were summarized, and it is known that the predicted value of the prediction model built in this study was closer to the actual value, proving the model's efficacy.

## 2. Methodology

This study examined mental health monitoring and abnormality analysis for elite athletes based on their dynamic threshold. The secondary data were gathered from scholarly journals, books, and websites. Secondary data from scholarly publications, books, and websites were compiled to develop the study's theoretical framework. To accomplish the study's purpose, the current study first described the flow of the dynamic mental health monitoring for sports majors and offered the prediction flow of the proposed model.

After the prediction flow of the suggested model, the Gradient Boosting Decision Tree (GBDT) model was used to predict the mental health level of college students majoring in sports. In addition, the subsequent stage involves data preparation and preprocessing. After indicating the mental health level of college students majoring in sports, this study compiled and analyzed data. Other procedures included model training and prediction error computation in this study. In addition, the sliding window method with a dynamic threshold was described. Before describing the structure and concept of the proposed prediction model, this research employed a non-parametric dynamic threshold setting to detect the local abnormality in the evaluation data series of the mental health level for sports majors.

## 3. Flow of Mental Health Monitoring for Sports Majors

The mental health evaluation of sports majors is the systematic and in-depth diagnosis of a single psychological condition and mental disease of sports majors by the acquisition of complete and up-to-date records of psychological tests and interviews with sports majors. The objective is to make prompt adjustments and corrections to the psychological issues of sports majors.

Using questionnaires and the current mental health scale, this research provides a comprehensive assessment of the mental health of sports majors. After conquering the psychological issues or barriers faced by sports majors, the writers documented the pertinent material and compiled comprehensive psychological archives, providing psychological counselors and psychologists with valuable evaluation resources. Figure 1 depicts the flow of dynamic mental health monitoring for elite athletes. The writers created all figures in the article, and the data in the tables represent the results of our survey and study.

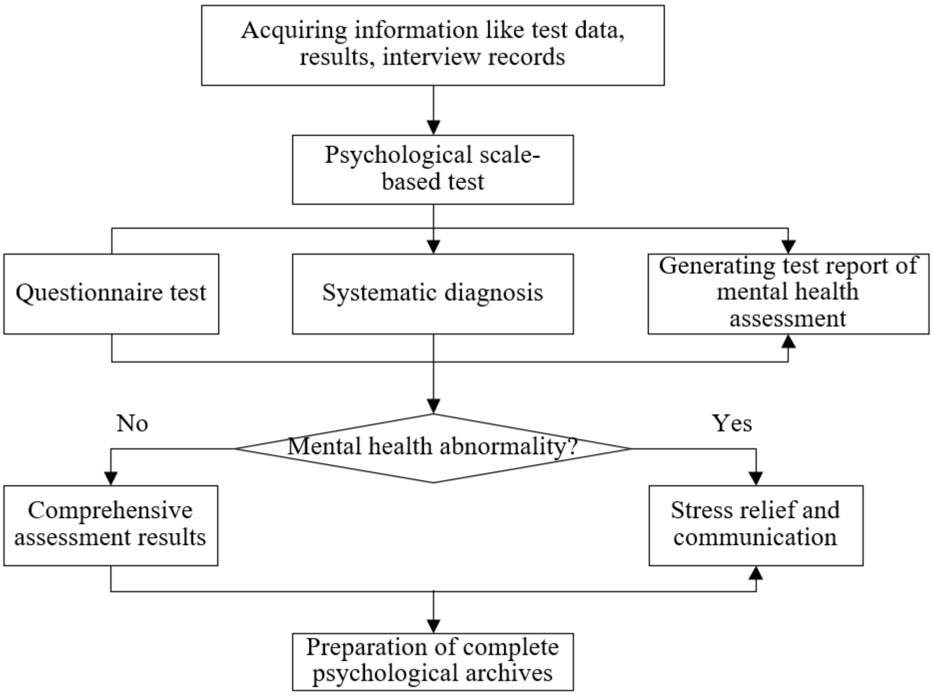



***Figure 1.*** The flow of dynamic monitoring of the mental health of sports majors

Corrections are made to the existing mental health scales, including 1) intelligence measures of IQ, creativity, observation, and imagination; 2) mental health measures of self-assessed anxiety, depression, and stress relief ability, etc.; and 3) other types of psychological measures, such as love fitness, interpersonal relationship processing, and personal planning ability. After the sport's majors completed the test, the test scores were weighted to provide a mental health assessment test report. Then, the psychological irregularities were automatically cautioned and reported. The mental health detection and warning method is described in the following parts.

## 4. Processing of Test Data and Error Calculation

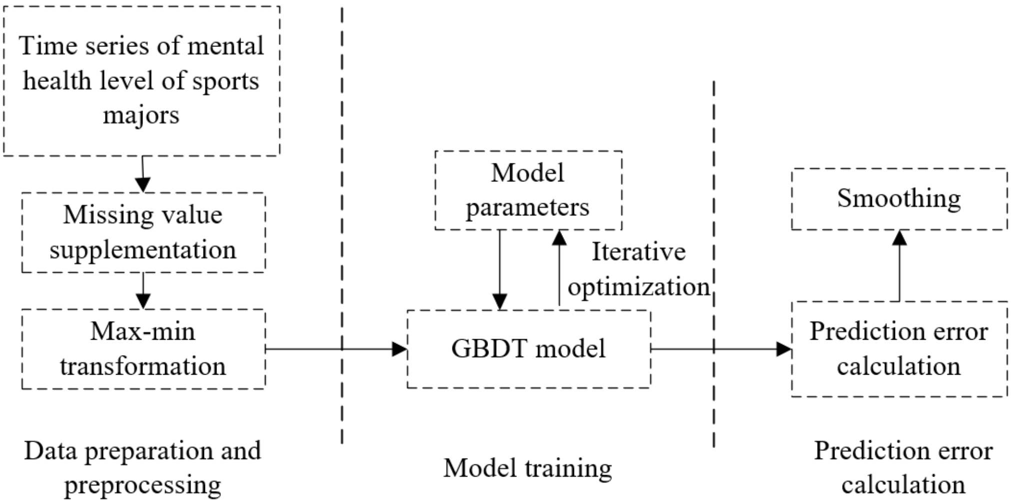



***Figure 2.*** The flow of model prediction

Mental health levels of sports majors form a time series with a single variable. In this research, a gradient-boosting decision tree (GBDT) is created to predict the mental health of sports majors against each scale and to anticipate the mental health level at the future moment based on a particular data series length. The prediction error is the difference between the predicted and actual levels. Thus, we could monitor the real-time changes in the mental health of sports majors and discuss any odd conditions. Figure 2 depicts the model's prediction flowchart.

**Table 1**

*Data of mental health scale analysis*

| Student number | Analysis of monitoring results | | | | Data missing rate |
|---|---|---|---|---|---|
| | Maximum | Minimum | Mean | Standard deviation | |
| *S*1 | 139.2 | 157.2 | 162.584 | 4.1258 | 0.02152 |
| *S*2 | 105.7 | 94.2 | 96.372 | 4.632 | 0.06259 |
| *S*3 | 162.9 | 125.1 | 114.259 | 2.529 | 0.04157 |
| *S*4 | 152.5 | 82.6 | 136.281 | 3.625 | 0.05214 |
| *S*5 | 162.9 | 84.7 | 96.385 | 3.851 | 0.03629 |
| *S*6 | 107.2 | 91.9 | 91.241 | 4.285 | 0.04751 |
| *S*7 | 142.6 | 97.5 | 93.257 | 4.632 | 0.05281 |
| *S*8 | 174.2 | 93.1 | 98.352 | 3.285 | 0.03265 |
| *S*9 | 96.3 | 61.7 | 74.158 | 5.247 | 0.08472 |
| *S*10 | 94.2 | 77.4 | 85.296 | 2.321 | 0.05149 |

Table 1 presents the data from the mental health scale analysis. It can be seen that the missing rate for the collected data of the mental health scale from the sport's majors was lower than 1%. It is essential to ensure the temporal coherence of the sample data used in the GBDT to predict the mental health of sports majors. For this purpose, the mean value method was adopted to fill in the missing values, and the max-min transform was carried out so that the mental health scale data fell within the interval [-1, 1].

Let $A=\{a_1,a_2,...,a_o\}$ be the data of the mental health scale for sports majors; $o=(1,2,...,m)$ be the index data on the mental health level of sports majors, with m being the length of the dataset. Then, the maximum and minimum were taken from A, corresponding to 1 and -1, respectively. Suppose $max=max\{a_1,a_2,...,a_o\}$and $min=min\{a_1,a_2,...,a_o\}$, $-1\leq a^i{}_o\leq 1$ is the value after max-min transform, and $A'=\{a'_1, a'_2,...,a'_o\}$, $o=(1,2,...,m)$ is the transformed dataset. The other data can be mapped to the interval (-1,1) by:

$$a_o' = 2\frac{a_o-min}{max-min} - 1 \quad (1)$$

The max-min transformation of the prediction results can be expressed as:

$$\hat{b}_o = min + \frac{\hat{b}'_o+1}{2}(max - min) \quad (2)$$

If the forecast dimensionality is too high, the prediction error will be significant. This research trains the model with the sport's critical samples on varying mental health levels to resolve the issue. Separately, the trained models were used to evaluate the mental health of sports majors with comparable psychological test experience:

$$A = \left\{\begin{bmatrix} a_1^{(o-k_r)} \\ a_2^{(o-k_r)} \\ \cdots \\ a_n^{(o-k_r)} \end{bmatrix}, \ldots, \begin{bmatrix} a_1^{(o-1)} \\ a_2^{(o-1)} \\ \cdots \\ a_n^{(o-1)} \end{bmatrix}, \begin{bmatrix} a_1^{(o)} \\ a_2^{(o)} \\ \cdots \\ a_n^{(o)} \end{bmatrix}, \begin{bmatrix} a_1^{(o+1)} \\ a_2^{(o+1)} \\ \cdots \\ a_n^{(o+1)} \end{bmatrix}\right\} \quad (3)$$

The prediction matrix of the model is denoted by $A=\{a^{(1)},a^{(2)},...,a^{(t)}\}$, $o=1,2,...,m$, $a^{(o)}\in R^n$. $\{a_1^{(1)},a_2^{(2)},...,a_n^{(o)}\}$ is an n-dimensional column vector at time o. At time o, the number of predictions for the series after that time is characterized by the series length $k_r$. Then, the length of the series predicted at time o is denoted by $k_t$.

The rationality of the loss function used by the model determines how close the predicted value is to the true value. The loss function used to train our model can be expressed as:

$$MSE = \frac{\sum_{i=1}^{m}(\hat{b}_i'-a_i')^2}{m} \quad (4)$$

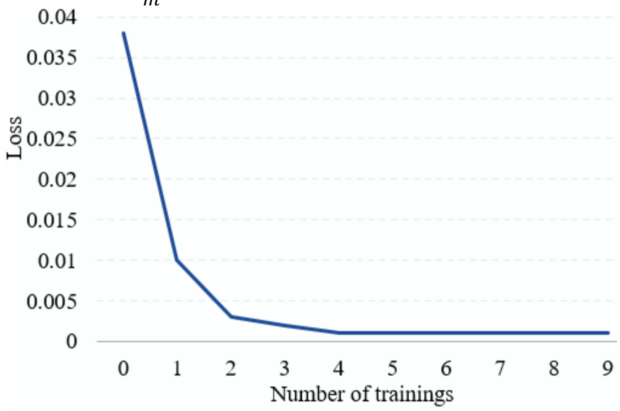



***Figure 3.*** The trend of loss with the number of training

Figure 3 shows the trend of the loss of the samples with the number of training. The loss gradually tended to be stable after the number of training surpassed 4, suggesting that the model training is converging. Hence, this paper decides to train the model five times before predicting the primary sports data of the mental health scale.

Suppose the model can learn the features of sports major data of mental health scale and obtain the ideal fitting effect. In that case, the predicted mental health levels of sports majors obtained from the time variation of historical data can, to a certain degree, reflect the mental health levels of these subjects under general conditions. Considering the physical meaning of the data, it is scientific and practical to detect the abnormal period of sports significant mental health based on the error outputted by the model. Let $s^{(o)}$ be the prediction error of GBDT at time o; $b^{(o)}$ be the actual value ($b^{(o)}=as_i^{(o+1)}$) at time $o$+1; $b\wedge^{(o)}$ be the predicted value by GBDT at time o+1. Then, we have:

$$s^{(o)} = \left|b^{(o)} - \hat{b}^{(o)}\right| \quad (5)$$

Let f be the length of the sliding window f, which determines the length of the error vector. Then, the predicted mental health level of sports majors after a specific continuous time interval is introduced into the error vector of the sliding window and can be expressed as:

$$s = \left[s^{(o-f)}, \ldots, s^{(o-k)}, \ldots, s^{(o-1)}, s^{(o)}\right] \quad (6)$$

The prediction error of sports major mental health will peak if the mental health level is not completely predicted. To prevent the problem, the exponentially weighted average method was adopted to smooth the obtained s. The smoothed error vector is represented by $s_r=[s_r^{(o-f)},..,s_r^{(o-k)},...,s_r^{(o-1)},s_r^{(o)}]$.

## 5. Dynamic Threshold and Prediction Model

The evaluation data on the mental health levels of sports majors form a time series that oscillates by a specific law. This paper adopts non-parametric dynamic thresholding to detect the local anomalies in the evaluation data series of the mental health level for sports majors. For each sliding window, a threshold that changes with the change of o is used to identify abnormal series.

This paper chooses the parameter that guarantees the maximum judgment formula as the threshold. Thus, the penalty term was introduced into the judgment formula to eliminate the influence of the oscillation of the s value. Let X be the set of parameters; $\lambda(s_r)$ and $\varepsilon(s_r)$ be the mean and variance of the error series after smoothing, respectively; P is a set of orderly positive values; x be the element representing the mean of the smoothed error series with p times the standard error. The relevant calculation process can be expressed as follows:

$$X = \{x | x = \lambda(s_r) + p\varepsilon(s_r)\} \quad (7)$$

$$p \in P, P = \{p | 2 + 0.5m, m \in M +\} \quad (8)$$

$$x = argmax(X) = \frac{\dfrac{\Delta\lambda(s_r)}{\lambda(s_r)} + \dfrac{\Delta\varepsilon(s_r)}{\varepsilon(s_r)}}{|s_x| + |S_{seq}|^2},$$
$$\Delta\lambda(s_r) = \lambda(s_r) - \lambda(\{s_r^i \in s_r | s_r^i < x\}),\ \Delta\varepsilon(s_r) = \varepsilon(s_r) - \varepsilon(\{s_r^i \in s_r | s_r^i < x\})$$
$$s_x = \{s_r^i \in s_r | s_r^i > x\},\ S_{seq} = the\ subset\ with\ continuous\ i\ in\ set\ s_x$$
$$i = o - f, \ldots, o - k_r, \ldots, o - 1, o \quad (9)$$

The calculation of formula (9) can effectively reduce the influence of the mean value of $s_r$ on the selected threshold.

The abnormality detection of mental health for college students is a kind of unsupervised abnormality detection. Therefore, this paper scores and ranks the abnormality of the analyzed abnormal series to understand the severity of sports major mental health problems in various aspects. Let $s^{(i)}_{sub}$ be the subset of set $S_{sub}$; $m$ be the number of consecutive series in the set $S_{sub}$; $s^{i}_{sub}$ be the i-th consecutive series. Then, the abnormality score $r^{(i)}$ of the i-th consecutive series, whose smoothing error is greater than the selected threshold, can be calculated by:

$$r^{(i)} = \frac{max\left(s_{sub}^{(i)}\right) - argmax(X)}{\lambda(s_r) + \varepsilon(s_r)}, i = 1,2, \ldots, m \quad (10)$$

Because the anomalous continuous series in each sliding window were scored only once, and because the abnormal series could span many windows, they were separated into multiple scoring segments. This paper merged the multi-segment abnormality scores of the abnormal series, calculated the weighted mean of multiple abnormality scores, and used the result as the abnormality score for this series to maintain time continuity.

The GBDT incorporates the advantage of decision tree regression into the gradient boost framework. The structure of GBDT can be compared to a powerful learner made up of numerous essential learners. This article increases the GBDT model's ability to predict the mental health level of sports majors. Let l be the number of independent variables or test items on the mental health scale, and let m represent the number of mental health scale samples. Consequently, the sample dataset C can be stated as follows:

$$C = \{a_i, b_i\}^m = \begin{pmatrix} a_{11} & \cdots & a_{1k} & b_1 \\ a_{21} & \cdots & a_{2k} & b_2 \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{ml} & b_m \end{pmatrix} \quad (11)$$

Let $G^*(a)$ be the prediction function; a be the independent variable; b be the dependent variable; $SQ(b, G(a))$ be the loss function that maps from a to b. The training objectives of the regression model are to optimize $G^*(a)$ and minimize $SQ(b, G(a))$:

$$G^*(a) = arg\min_{G(a)} S_{b,a}\left[SQ\left(b, G(a)\right)\right] \quad (12)$$

$$SQ\left(b, G(a)\right) = \left(b - G(a)\right)^2 \quad (13)$$

Suppose the parameter of $G(A)$ is $Z=\{Z_1,Z_2,\ldots\}$, which satisfies $Z=\{\gamma_n,\beta_n\}^N_0$. The n-th basic learner can be expressed as $\gamma_n f(a;x_n)$, the n-th regression tree in $G^*(a)$ can be expressed as $f(a;x_n)$, the parameter of the n-th regression tree can be expressed as $\beta_n$, and the weight of the n-th regression tree in $G(A)$ can be expressed as $\gamma_n$. Then, formula (13) can be rewritten as the superposition of multiple basic learners:

$$G(a, Z) = \sum_{n=0}^{N} \gamma_n f(a, \beta_n) \quad (14)$$

For $m$ samples$\{a_i, b_i\}^m$, the optimization of $G^*(a)$ is to find the best $(\gamma_n,\beta_n)$:

$$(\gamma_n, \beta_n) = \underset{\beta,\gamma}{argmin} \sum_{i=1}^{m} SQ\big(b_i, G_{n-1}(a_i) + \gamma f(a;\beta)\big) \quad (15)$$

Firstly, a constant σ is assigned to initialize the basic learner to minimize the current loss function. The corresponding prediction function $G_0(a)$ can be given by:

$$G_0(a) = \underset{\sigma}{argmin} \sum_{i=1}^{m} SQ(b_i, \sigma) \quad (16)$$

To speed up the loss reduction during model execution, this paper constructs the n-th basic learner $\gamma_n f(a;\beta_n)$ in the gradient descent direction of the loss function generated by the first n-1 iterations. The prediction function after the n-th iteration of the model is denoted by $G_n(a)$, and the corresponding loss function by $SQ(b, G_n(A))$. Then, the construction direction of $-h_n(a_i)$, the n-th primary learner, can be constructed based on $SQ(b, G_n(A))$:

$$-h_n(a_i) = -\left[\frac{\partial SQ(b_i, G(a_i))}{\partial G(a_i)}\right]_{G(a_i)=G_{n-1}(a_i)} \quad (17)$$

Parameters $\gamma_n$ and $\beta_n$ can be further derived from $-h_n(a_i)$. Along that direction, the parameter approximated by the regression tree $f(a;\beta_n)$ and the optimal step length are denoted by $\beta_n$ and $\gamma_n$, respectively:

$$\beta_n = \underset{\beta,\gamma}{argmin} \sum_{i=1}^{m} [-h_n(a_i) - \gamma f(a;\beta)]^2 \quad (18)$$

$$\gamma_n = \underset{\gamma}{argmin} \sum_{i=1}^{m} SQ\big(b_i, G_{n-1}(a_i) + \gamma f(a;\beta_n)\big) \quad (19)$$

The model will stop executing after the convergence condition, or the maximum number of iterations is satisfied, and the final prediction model can be expressed as $G_n(a)=G_{n-1}(a)+\gamma_n f(a,\beta_n)$. To reduce the probability of overfitting in model training, the learning rate η is introduced, and the prediction model can be updated as:

$$G_n(a) = G_{n-1}(a) + \eta\gamma_n f(a;\beta_n), 0 \le \eta \le 1 \quad (20)$$

## 6. Model Verification

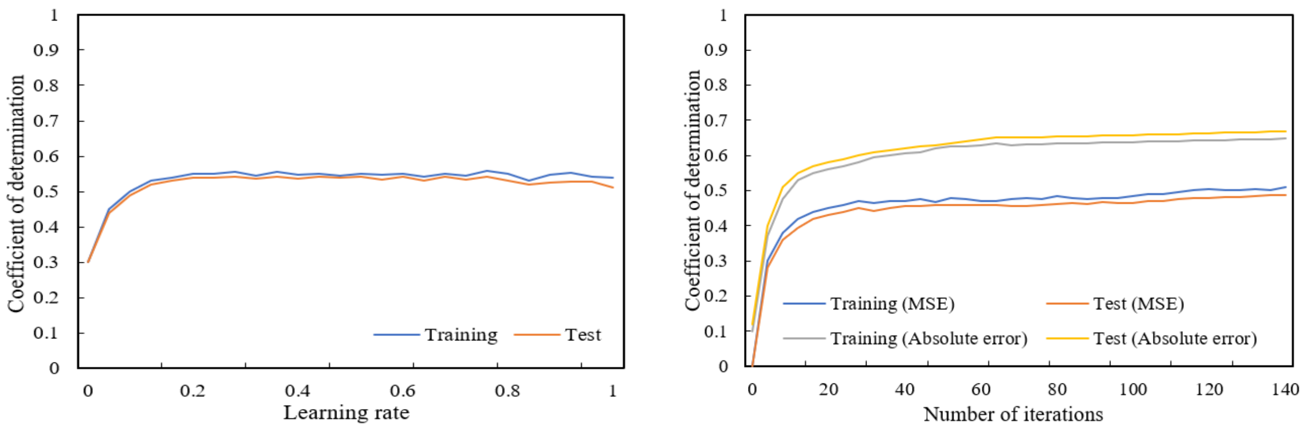
To verify its superiority in prediction, the proposed prediction model was compared with common predictors, namely, the linear regression model, backpropagation (BP) neural network, support vector machine (SVM), and Kalman filter denoted by 1-4 in turn. Table 2 compares the prediction results of the five models. According to the table, the evaluation errors of the proposed model were the lowest, its $r^2$-value was the highest, and its prediction performance was better than other models.

**Table 2**

*Prediction results of the five models*

| Model number | Metric | | | |
|---|---|---|---|---|
| | *MAE* | *RMSE* | *MAPE* | $r^2$ |
| 1 | 0.928 | 1.581 | 1.418 | 0.326 |
| 2 | 0.915 | 1.629 | 1.205 | 0.374 |
| 3 | 1.327 | 1.352 | 1.372 | 0.312 |
| 4 | 0.813 | 1.528 | 1.697 | 0.495 |
| Our model | 0.795 | 0.852 | 0.753 | 0.588 |

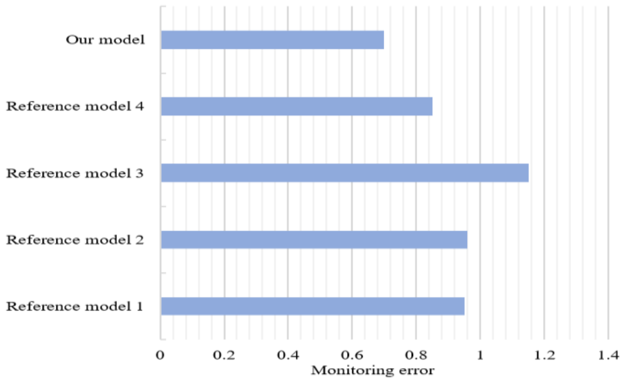
Note: MAE, RMSE, and MAPE are short for mean average error, root means square error, and mean absolute percentage error, respectively.



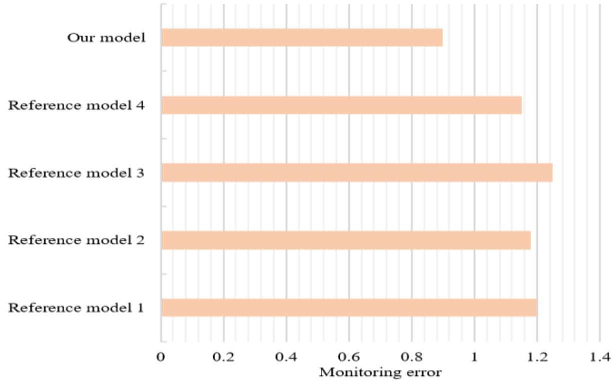

(1) Variation in learning rate (2)Variation with error type

***Figure 4.*** Variation of coefficient of determination with learning rates and number of iterations for different models

This research uses the training set, and test set coefficients of determination as the training effect metric for our model. The coefficients reflect the quality of model prediction under various parameter settings. Figure 4 illustrates the correlation between the coefficient of determination, learning rates, and iterations for several models. The coefficient grew with the learning rate and tended to stabilize once the learning rate reached 0.25. The choice of loss function also substantially impacted the effectiveness of the model prediction. The coefficient representing the MSE was less than the absolute error coefficient. Figure 5 summarizes the output error of various models. Compared to the four contrastive models, our model has a fundamental modest mistake and MSE, as well as a high $r^2$. Therefore, the value predicted by our model is closer to the actual value than any competing model's prediction.




(a) MSE




(b) Absolute error

***Figure 5.*** Output errors of different models

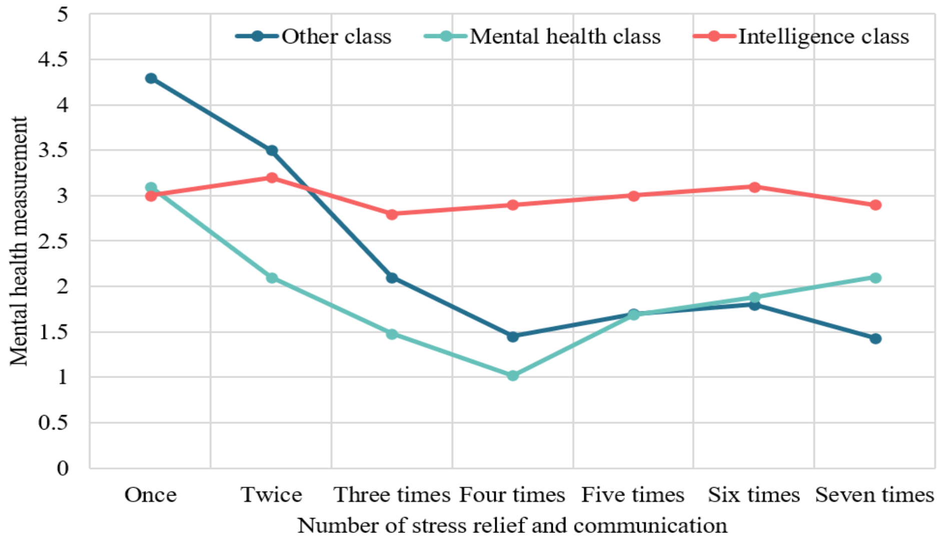



***Figure 6.*** The trend of mental health of sports majors after stress relief and communication

Our methodology offers excellent analysis and forecasting of the mental health trend of sports majors who have received stress release, communication, and other psychological consultation or therapy. Figure 6 depicts the mental health trajectory of sports majors following stress reduction and communication. As shown in Figure 6, the more stress alleviation and communication with psychological counselors and psychologists sports majors engage in, the better their bad mental health. However, new pressures would result in a new inclination toward mental illness. Under certain circumstances, it is necessary to comprehend the mental health state of sports majors in different situations in real time and to ensure a specific monitoring frequency to provide the required reference to real-time psychological intervention for sports majors with mental health issues at different learning stages.

## 7. Conclusions

This research investigates mental health monitoring and abnormality analysis for athletes based on a dynamic threshold. The authors first described the flow of the dynamic mental health monitoring for sports majors, the prediction flow of the proposed model, and the research methods, including data preparation and preprocessing, model training, and prediction error calculation. Before describing the structure and concept of the suggested prediction model, the non-parametric dynamic threshold setting was utilized to identify the local abnormality in the evaluation data series of the mental health level for sports majors. The suggested prediction model was compared with common predictors, including the linear regression model, BP neural network, SVM, and Kalman filter. The variation of the coefficient of determination was observed concerning learning rates and the number of iterations across models. The findings demonstrate that the suggested model predicts a value closer to the actual value than any competing model. In addition, the authors summarized the mental health trend of sports majors following stress alleviation and communication. The results demonstrate that our model can accurately analyze and predict the mental health trend of sports majors who have received stress release, communication, and other psychological consultation or treatment.

Even though this paper employed a dynamic threshold to detect abnormality based on the prediction of univariate and multivariate models and obtained good results, the period and numerical changes were compatible with actual conditions. In future research, it will be necessary to combine external data with internal data to identify the causes of abnormal output, the data saved during equipment operation could be increased by increasing the number of dataset variables, and the concept of exclusion could be adapted to lock the causes of abnormal data value further.

**7.1 Implications of the Study**

The current study examined mental health monitoring and abnormality analysis for sports majors based on a dynamic threshold, making a substantial contribution to the mental health literature. Numerous research has addressed mental health monitoring; however, mental health monitoring in conjunction with anomaly analysis is rarely discussed in the literature. Rarely is the combined function of health monitoring and abnormality analysis the subject of a single study. This study is, therefore, of great value because it contributes to the existing body of knowledge. Likewise, the literature rarely considers sports majors based on a dynamic threshold. Thus, integrating mental health monitoring, anomaly analysis, and sports major based on dynamic thresholds significantly impacts the body of knowledge. In addition, authorities should consider these findings when evaluating the mental health of college students. Considering this study's findings, policymakers can devise various initiatives to enhance the mental health of college students.

**7.2 Limitations and Future Directions**

This study has a few limitations, even though the topic of mental health monitoring and abnormality analysis for sports majors based on dynamic thresholds has made an extraordinary contribution to the body of literature. This study's limitations could represent potential future directions. For example, this study focused solely on the mental health of college students. Alternatively, students' mental health in schools and universities is equally crucial. Particularly, school-related mental health difficulties have long-term effects; consequently, future research should focus on the mental health of students from schools and universities. In addition, this study focused on the mental health of the sport's major, limiting its breadth. Thus, future research should expand its reach to include the mental health of all pupils.

## References


Bork, S. J., & Mondisa, J. L. (2022). Engineering graduate students' mental health: A scoping literature review. *Journal of Engineering Education, 111*(3), 665-702. https://doi.org/10.1002/jee.20465

Chen, M., & Jiang, S. (2019). Analysis and research on mental health of college students based on cognitive computing. *Cognitive Systems Research, 56*, 151-158. https://doi.org/10.1016/j.cogsys.2019.03.003

Danowitz, A., Benson, B., Callenes-Sloan, J., & Hummel, P. (2018). Differences in Mental Health between Students in a Jointly Offered Computer Engineering Program and the two Home Departments. In *2018 IEEE Frontiers in Education Conference (FIE)* (pp. 1-5). IEEE. https://doi.org/10.1109/FIE.2018.8658520

Dong, Y. (2019). Comprehensive evaluation analysis of mental health status of poverty-stricken college students at present age with interval-valued intuitionistic fuzzy information. *Journal of Intelligent & Fuzzy Systems, 37*(2), 2027-2034. https://doi.org/10.3233/IFS-219217

Fu, Q. (2022). Dynamic Modeling of Influencing Factors and Change Trend of College Students' Mental Health Based on Big Data. *Scientific Programming, 2022*, 4127924. https://doi.org/10.1155/2022/4127924

Gao, H. (2022). Research on the Construction of College Students' Mental Health Security System. *Journal of Healthcare Engineering, 2022*, 4001603. https://doi.org/10.1155/2022/4001603

Hou, J. (2022). Effective Ways for College Students' Mental Health Education Based on Music Therapy. *Journal of Healthcare Engineering, 2022*, 3031064. https://doi.org/10.1155/2022/3031064

Hu, F., Xi, X., & Zhang, Y. (2021). Influencing mechanism of reverse knowledge spillover on investment enterprises' technological progress: An empirical examination of Chinese firms. *Technological Forecasting and Social Change, 169*, 120797. https://doi.org/10.1016/j.techfore.2021.120797

Hussna, A. U., Trisha, I. I., Ritun, I. J., & Alam, M. G. R. (2021). COVID-19 impact on students' Mental Health: Explainable AI and Classifiers. In *2021 International Conference on Decision Aid Sciences and Application (DASA)* (pp. 847-851). IEEE. https://doi.org/10.1109/DASA53625.2021.9682371

Li, D. (2022). The Design of the Mental Health Test System for College Students Based on Android Platform Technology. In *The 2021 International Conference on Machine Learning and Big Data Analytics for IoT Security and Privacy: SPIoT-2021 Volume 2* (pp. 895-900). Springer. https://doi.org/10.1007/978-3-030-89511-2_123

Li, G., & Wu, X. (2022). Effect of Sandplay Therapy on the Mental Health Level of College Students. *Computational and Mathematical Methods in Medicine, 2022*, 3716849. https://doi.org/10.1155/2022/3716849

Li, K., & Yu, W. (2021). A Mental Health Assessment Model of College Students Using Intelligent Technology. *Wireless Communications and Mobile Computing, 2021*, 7485796. https://doi.org/10.1155/2021/7485796

Li, P. (2022). The Mental Health Evaluation System of College Students Based on Data Mining. *Scientific Programming, 2022*, 3800169. https://doi.org/10.1155/2022/3800169

Liu, X. (2022). Optimization of College Students' Mental Health Education Based on Improved Intelligent Recognition Model. *Mathematical Problems in Engineering, 2022*, 1573810. https://doi.org/10.1155/2022/1573810

Mantzios, M., Cook, A., & Egan, H. (2019). Mental health first aid embedment within undergraduate psychology curriculums: an opportunity of applied experience for psychology students and for enhancing mental health care in higher education institutions. *Higher Education Pedagogies, 4*(1), 307-310. https://doi.org/10.1080/23752696.2019.1640631

Mao, S., & Liu, S. (2022). Model Analysis of Applying Computer Monitoring to College Students' Mental Health. *Journal of Sensors, 2022*, 4960465. https://doi.org/10.1155/2022/4960465

Mitchell, K. M., Holtz, B. E., & McCarroll, A. M. (2022). Assessing college students' perceptions of and intentions to use a mobile app for mental health. *Telemedicine and e-Health, 28*(4), 566-574. https://doi.org/10.1089/tmj.2021.0106

Saadoon, K. J., Muhlis, M., & Mohammed, R. O. (2022). Architecture students' satisfaction in Iraqi private universities: TIU-S in focus. *International Journal of Sustainable Development and Planning, 17*(4), 1349-1354. https://doi.org/10.18280/ijsdp.170432

Vella, S. A., Aidman, E., Teychenne, M., Smith, J. J., Swann, C., Rosenbaum, S., White, R. L., & Lubans, D. R. (2023). Optimising the effects of physical activity on mental health and wellbeing: a joint consensus statement from sports medicine Australia and the Australian Psychological Society. *Journal of Science and Medicine in Sport*. https://doi.org/10.1016/j.jsams.2023.01.001

Wang, F. (2020). The Application of MOOC in College Students' Mental Health Teaching. In V. Sugumaran, Z. Xu, & H. Zhou (Eds.), *Application of Intelligent Systems in Multi-modal Information Analytics* (pp. 546-551). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-51556-0_79

Wang, F. (2022). College Students' Mental Health Analysis Based on Clustering Analysis Algorithm. In *Innovative Computing* (pp. 1333-1341). Springer. https://doi.org/10.1007/978-981-16-4258-6_162

Wang, Y., & Ma, C. (2022). Evaluation and Analysis of College Students' Mental Health from the Perspective of Deep Learning. *Wireless Communications and Mobile Computing, 2022*, 5687003. https://doi.org/10.1155/2022/5687003

Wiljer, D., Johnson, A., McDiarmid, E., Abi-Jaoude, A., Ferguson, G., Hollenberg, E., van Heerwaarden, N., Tripp, T., & Law, M. (2017). Thought Spot: Co-Creating Mental Health Solutions with Post-Secondary Students. *Studies in health technology and informatics, 234*, 370-375. https://doi.org/10.3233/978-1-61499-742-9-370

Williams, L., & Washington, G. (2018). Soul Glow: an application for helping to understand and improve mental health care of HBCU students. In *2018 IEEE International Conference on Healthcare Informatics (ICHI)* (pp. 358-360). IEEE. https://doi.org/10.1109/ICHI.2018.00055

Wu, Y., & Zhang, F. (2023). The health cost of attending higher-achievement schools: Peer effects on adolescents' academic performance and mental health. In *The Frontier of Education Reform and Development in China: Articles from Educational Research* (pp. 211-240). Springer. https://doi.org/10.1007/978-981-19-6355-1_12

Xun, M. (2021). Establishing Early Warning System of College Students' Mental Health Based on System Dynamics. In *2021 International Symposium on Advances in Informatics, Electronics and Education (ISAIEE)* (pp. 38-41). IEEE. https://doi.org/10.1109/ISAIEE55071.2021.00017

Yousef, I. A., Kilani, H. A., Mo'ath, F., Al-Nawayseh, A., Al-Za'abi, A., Belghali, M., Alnuaimi, J., Shaheen, W. M., & Liftawi, S. M. (2022). Social Issues During the COVID-19 Quarantine Period: Interaction of Physical Activity and Mental State. *International Journal of Sustainable Development and Planning, 17*(3), 777-785. https://doi.org/10.18280/ijsdp.170308

Zhao, H. (2021). Intelligent Evaluation System of College Students' Mental Health Based on Mobile Terminal. In *2021 IEEE International Conference on Industrial Application of Artificial Intelligence (IAAI)* (pp. 162-168). IEEE. https://doi.org/10.1109/IAAI54625.2021.9699926

Zheng, W. (2022). Cluster Analysis Algorithm in the Analysis of College Students' Mental Health Education. *Applied Bionics and Biomechanics, 2022*, 6394707. https://doi.org/10.1155/2022/6394707