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Article

Integrating Heart Rate Variability and Exercise Load for Early Warning of Overtraining Syndrome

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Abstract: Objective To develop an early warning model for overtraining syndrome (OTS) and provide OTS patients with a targeted and practical risk assessment tool, thereby reducing the incidence of OTS among athletes undergoing long-term excessive training and improving the quality of personalized care. Methods Seventy-two patients with OTS were selected. Eight indicators, including training load and heart rate variability, were chosen as model inputs. Relevant risk factors were identified using LASSO regression analysis, and early warning models were constructed using machine learning methods such as logistic regression and gradient boosting classifiers. Model performance was evaluated using metrics such as AUC, accuracy, sensitivity, and specificity, while calibration curves and receiver operating characteristic (ROC) curve analysis were employed to assess the model's calibration and clinical utility.Results: Variables were screened via LASSO regression analysis, ultimately identifying eight factors—including training load and heart rate variability—as potential risk factors. The logistic regression model demonstrated the best performance (AUC = 0.841; 95% CI: 0.780–0.898) and demonstrated good clinical utility in both calibration curve and decision curve analyses. Conclusion: The OTS early warning model developed in this study facilitates the long-term, systematic collection of physiological data from athletes undergoing prolonged excessive training, promotes the clinical translation of early warning models, screens for high-risk OTS patients, guides nursing practice, and effectively reduces the incidence of OTS.

Keywords: Overtraining syndrome; risk prediction; excessive exercise; machine learning models; risk factors

1. Introduction

During the process of sports training, in order to meet higher training requirements and achieve stronger abilities and competitive performance, coaches usually require athletes to adapt to their maximum capabilities. During this process, athletes may experience overall fatigue or impaired athletic performance. This situation is currently generally recognized as fatigue (OR) [1]. If this condition persists for several months or longer, it can be diagnosed as overtraining syndrome (OST) [2-3]. Brel et al. believe that OST is a pathological state caused by a long-term imbalance between training and recovery, resulting in a continuous decline in athletic performance for several weeks to several months and serious damage to the athlete's health [4]. However, currently, OST lacks clear and reliable early biochemical or functional markers, and diagnosis mostly relies on retrospective determination, and the pathogenesis is also unclear. Kreher and Schwartz believe that overtraining syndrome is an adverse reaction of athletes to excessive exercise and insufficient recovery, involving multiple systems such as the neuro-endocrine-immune system disorder. The diagnosis of this disease still belongs to the clinical category, and it is mainly based on medical history and limited serological examinations [5]. Cardoos pointed out that functional overloading (FOR) recovery can improve athletic performance, non-functional overloading (NFOR) recovery takes several days to several weeks, while OST recovery takes several weeks or several months. Effectively distinguishing these three can help optimize training load and prevent OST [6]. Cadegiani and Kater found that compared with healthy athletes, the basal hormone levels of athletes with OST/FOR/NFOR were mostly normal; however, in stimulation tests (especially under conditions of excessive exercise), the responsiveness of growth hormone and adrenocorticotropic hormone was significantly weakened, the results of cortisol and catecholamines were inconsistent, and the responses of other hormones were normal [7]. Current research mostly focuses on overtraining rather than OST, and its pathogenesis and management still need to be further explored to improve the scientific assessment, education, and prevention of athletes.

In addition, Armstrong et al. believe that OST results from complex interactions of multiple systems, so they suggest using system methods such as network physiology, cross-omics analysis, and machine learning to integrate factors such as brain neural networks, HPA axis, gut microbiota, immunity, and energy metabolism to break through the bottlenecks of OST diagnosis, markers, and treatment [8]. In terms of the practical operation and risk prevention of athletes, Carfagno and Hendrix pointed out that competitive athletes may develop from excessive loading to OST when there is an imbalance between training and recovery, leading to a continuous decline in athletic performance or even ending their careers. Identifying markers related to excessive loading/overtraining, screening tests, and "red alert" signals can help break the negative cycle and prevent the occurrence of OST [9]. In terms of diagnostic indicator research, Carrard et al. identified several potential diagnostic indicators for OST, including hormones, neurotransmitters, psychological questionnaires, exercise tests, heart rate variability, electroencephalogram, immunity, and body composition, and emphasized the multi-system nature of OST, providing multi-dimensional evidence for the exclusion diagnosis of OST in clinical practice [10]. From the perspective of disease characteristics and prevention principles, Kreher believes that OST is a physiological maladaptive state that occurs in the context of excessive exercise and insufficient recovery, the cause and pathogenesis are still unclear, and the symptoms involve multiple systems such as hormones, immunity, nerves, and psychology, although there are no validated diagnostic and prevention methods, prevention remains the key [11]. In terms of the understanding of the pathogenic mechanism, Cadegiani and Kater believe that OST is not caused solely by overtraining, but is a "contradictory adaptation" process caused by chronic energy deprivation, gradually causing athletes to lose their physical fitness, which changes the previous single view of attributing OST to overtraining [12]. As for the existing problems, Weakley et al. found that currently, there is a lack of objective evidence to describe the performance decline and psychological symptom changes of OTS from a healthy state to the onset over a period of more than four weeks. The main obstacles include ambiguous terminology, difficulties in long-term monitoring, and the absence of prospective tests. It is urgent to develop a routine test combination in real scenarios to advance the scientific understanding of OTS [13].

The widespread application of artificial intelligence technology has promoted the intelligent and information-based innovation in the field of nursing. Among them, machine learning (ML) as the core technology of artificial intelligence can extract patterns from large amounts of data through different algorithms to improve the accuracy and stability of predictions [14-15]. Clinical prediction models are widely used in disease diagnosis, prognosis assessment, and risk stratification. Their forms include clinical prediction rules, prognostic models, and risk scores, mainly using parametric, semi-parametric, or non-parametric mathematical models to estimate the current risk of an individual's illness or the possibility of future adverse events [16]. Regarding the application of ML in early disease warning, Muralitharan et al. conducted a study and showed that the traditional weighted early warning system based on vital signs can initially screen the risk of patient deterioration, while machine learning models can capture the complex correlations between vital sign changes and parameters, and demonstrate better predictive efficacy in various medical scenarios such as general wards, ICUs, emergency departments, and home care [17]. Oeschger et al. explored various early warning technologies for infectious diseases, covering artificial intelligence climate and cross-species spill-over risk prediction, public opinion and health data monitoring, sentinel animal disease monitoring, sewage epidemiological screening, public place biological aerosol sampling, and rapid and immediate detection and high-throughput diagnostic methods [18]. Chowdhury et al. based on the clinical data of 375 COVID-19 patients, used ML to screen lactate dehydrogenase, neutrophil ratio, lymphocyte ratio, hypersensitive C-reactive protein, and age as key predictive indicators for death, and constructed a nomogram prognostic model to provide reference for patient risk stratification [19]. Salehinejad et al. based on the longitudinal deterioration index of hospitalized patients, constructed a new ML prediction model; after data verification, the AUC of the ML model was significantly better than the traditional threshold model, and still maintained good predictive efficacy within 12 hours before the event, cross-validation showed excellent generalization ability, and had clinical application value [20]. After summarizing the relevant research literature, it was found that there are relatively few studies on ML in the early warning of OTS. Therefore, constructing an ML-based early warning model for OTS has important exploration value and innovation space.

This study collected demographic data, training load, athletic performance assessments, and clinical findings from 172 patients with OTS. Descriptive statistical analysis was used to examine the probability of OTS occurrence under long-term excessive exercise. In the regression analysis model, a correlation feature decomposition was performed on the sample sequence of OTS occurrence probability under long-term excessive exercise, and combined with a random probability distribution model to enable early warning of OTS. Concurrently, machine learning models such as logistic regression and gradient boosting classifiers were employed to perform feature clustering and robustness testing for the probability of OTS occurrence under long-term excessive exercise, thereby optimizing early warning systems for OTS under such conditions.

2. Clinical Data and Methods

2.1. Clinical Data

2.1.1. General Information

The cases observed were all athletes who visited the medical department of a sports training school from September 2023 to September 2025. There were a total of 72 cases. Among them, 43 were male and 29 were female. The training programs included 12 individual events such as track and field, weightlifting, swimming, martial arts, wrestling, and basketball. The age ranged from 16 to 24 years old, with an average of (18.23 ± 2.25) years. The training duration was from 3 months to 6.2 years, with an average of (3.13 ± 0.84) years. There were 12 first-class athletes, 44 second-class athletes, and 16 others.

2.1.2. Diagnostic Criteria

Based on relevant content from *Sports Medicine Supervision* and a review of the literature on overtraining syndrome (OTS), a set of clinical diagnostic criteria for OTS has been summarized, comprising three components: symptoms, signs, and laboratory tests.

Clinical Symptoms:

(1) No improvement in personal best performance throughout the training period, or performance during maximum effort exercise remaining below the personal best;

(2) Feeling fatigued (tired or very tired), experiencing muscle soreness, and changes in mood for at least 7 consecutive days;

(3) Low motivation for training;

(4) Exclusion of other medical conditions.

Clinical Signs:

(1) Persistent weight loss exceeding 1/30 of normal body weight, which does not recover after rest or eating;

(2) Resting heart rate increased by more than 12 beats per minute compared to normal;

(3) Weak response to exercise, or the presence of a continuous diastolic murmur and a trapezoidal response;

(4) Pain in the left hypochondrium may occur during exercise; upon examination, some patients may present with hepatosplenomegaly, though liver function is generally normal;

(5) Female patients may experience menstrual irregularities, with amenorrhea occurring in severe cases.

Laboratory Tests:

(1) The ratio of lactate to perceived exertion (RPE) (multiplied by 100) is less than 100.

(2) Electrocardiographic (ECG) changes, such as high left ventricular voltage, sinus bradycardia, and ST-segment and T-wave changes (marked ST-segment depression exceeding 0.075 mV).

(3) Arrhythmias, such as ventricular premature beats, paroxysmal tachycardia, and various conduction abnormalities.

(4) Atrioventricular conduction abnormalities, such as first-degree atrioventricular block, ectopic rhythms, second-degree atrioventricular block with type I changes (Wenckebach phenomenon), and bundle branch block.

A diagnosis of OTS can be confirmed in patients who exhibit all clinical symptoms, along with any one clinical sign and any one laboratory finding.

2.2. Methods

2.2.1. Feature Selection

(1) Training Load (TL)

The best way to determine an appropriate exercise intensity is to combine heart rate and RPE (Rating of Perceived Exertion). This involves first exercising within an appropriate heart rate range and then using the RPE scale during exercise to gauge intensity. However, the RPE scale is highly subjective; results may be influenced by personal perception or altered by external environmental factors. Therefore, the RPE scale is typically used in conjunction with other physiological and biochemical indicators.

(2) Heart Rate (HR)

Heart rate monitoring is one of the most commonly used tools for assessing an athlete's internal load. It is based on the correlation between heart rate during exercise and oxygen consumption efficiency at steady state. However, a percentage of maximum heart rate is often used to set and monitor intensity. Due to the influence of other controlling factors, such as hydration, environment, and medication, maximum heart rate may vary by up to 6.5%.

(3) Heart Rate to RPE Ratio (HR/RPE)

The ratio of these two indicators can help elucidate fatigue. Changes in the external environment can easily cause one indicator to fluctuate within a certain range. Furthermore, the accuracy of these indicators is subject to question due to tester error or misinterpretation; therefore, combining these related indicators can help provide early warning signs.

(4) Training Impulse (TRIMP)

TRIMP is generally considered a useful tool for assessing training load. It refers to the relationship between an individual's heart rate and the amount of physical work performed during a single training session, providing an effective heart rate-based assessment of exercise intensity. In addition, sport-specific TRIMP has been applied in running. Currently, sport-specific TRIMP is beginning to be used for early warning in soccer.

(5) Lactate Concentration (LAC)

Changes in LAC are particularly sensitive to exercise intensity and duration; however, lactate levels vary both between and within individuals. These variations depend on external temperature, body hydration status, diet, liver glycogen stores, pre-exercise activity level and muscle condition, as well as the time and location of blood sampling. Given the complexity of these influencing factors, blood lactate can also be combined with RPE; the ratio of blood lactate to RPE is analogous to the ratio of HR to RPE, and plays a crucial role in determining internal load and identifying fatigue or overtraining syndrome.

(6) Heart Rate Recovery (HRR)

HRR is the rate at which heart rate (HR) decreases after exercise ceases; it is considered an indicator of autonomic nervous system function and an athlete's training status. The autonomic nervous system comprises the sympathetic and parasympathetic nervous systems. During exercise, sympathetic nervous system activity increases while parasympathetic activity decreases, resulting in sympathetic dominance. HRR reflects a characteristic of cardiac autonomic function where sympathetic stimulation is withdrawn, leading to a decrease in activity and subsequent parasympathetic dominance.

(7) Heart Rate Variability (HRV)

HRV measured at rest or after exercise is used to indicate whether the body has adapted effectively to training. However, different testing methods and environmental conditions can lead to varying results. Research findings suggest that overtraining is associated with abnormal responses of the autonomic nervous system, which has sparked interest among some researchers in using HRV to diagnose OTS.

(8) Biochemistry, Hormones, and Immunology (Others)

Currently, numerous scholars are investigating the relationship between biochemistry, hormones, and immunology and exercise; however, no definitive biomarkers have been identified. At present, serum creatine kinase (CK) is the most commonly used biomarker, primarily due to the ease of sample collection and the maturity of analytical methods. A drawback is that it is easily influenced by muscle recovery time. At present, it appears that using biochemical, hormonal, or immunological markers to diagnose OTS is not yet a mature approach. Furthermore, sample preservation is difficult, and invasive sample collection is costly and technically challenging.

2.2.2. Data Processing

Class imbalance refers to a situation in classification tasks where there is a significant disparity in the number of samples across different classes. The degree of imbalance can be measured using the Imbalance Ratio (IR) metric. A higher IR value indicates greater imbalance. In such cases, evaluating a model's performance based on prediction accuracy without addressing the imbalance can cause the model to favor the majority class, resulting in lower accuracy. Currently, resampling or data synthesis is the most widely used and effective method for handling imbalanced datasets. Resampling methods can be divided into three categories: oversampling, undersampling, and mixed sampling. Oversampling methods are typically applied more frequently than other methods, and Synthetic Minority Oversampling Technique (SMOTE) is an improved algorithm within the category of random oversampling methods.

SMOTE is a powerful tool for handling imbalanced datasets. Its core principle involves analyzing samples from the minority class and manually synthesizing new samples based on them to add to the dataset, thereby making the ratio between the minority and majority classes more balanced. The advantage of SMOTE lies in its ability to effectively avoid overfitting compared to simple random oversampling. In our dataset, the heart rates and various feature values of professional athletes are 1.2 to 2.4 times higher than those of the general population, resulting in class imbalance. To address this issue, we employed the SMOTE oversampling technique to handle the imbalance in the minority class data, while leaving the majority class data unchanged. Ultimately, this expanded the number of samples in the minority class to match that of the majority class.

2.2.3. Model Development

Under conditions of prolonged excessive training, the probability data of OTS can be regarded as a sequence of probability analysis samples. By applying probability analysis sample sequence methods, we analyze the probability distribution of OTS characteristics under prolonged excessive training and assess the probability of athletes developing OTS under such conditions. The fitted state model describing the probability of athletes developing OTS under prolonged excessive training, as described by the characteristic equation, is as follows:

$$\begin{pmatrix} X \\ P(X) \end{pmatrix} = \begin{Bmatrix} a_1, a_2, ..., a_m \\ p(a_1), p(a_2), ..., p(a_m) \end{Bmatrix} \tag{1}$$

In this context, $0 \le p(a_i) \le (i = 0,1,2,...,m)$ and $\sum_{i=1} p(a_i)$ denote the feature parameters for the probability of athletes developing OTS under long-term excessive training, and the feature training subsets $S_i (i = 1,2,3,...,L)$ for each spatial solution vector—representing the probability of athletes developing OTS under long-term excessive training—satisfy the following conditions:

(1) $\sum = diag(\delta_1, \delta_2, ..., \delta_r)$, $\delta_i = \sqrt{\lambda_i}$, $\forall i \ne j$;

(2) $\bigcup_{i=1}^{L} S_i = V - u_s$;

(3) Let $x_{n+1} = \mu x_n (1 - x_n)$ be a conjugate solution of the sample sequence model for the probability of athletes developing OTS under long-term excessive training, satisfying the initial value eigenvalue decomposition conditions.

Based on the construction of a regression analysis model using prior information regarding the probability of athletes developing OTS under long-term excessive training, this study conducts an optimized design of an early warning model for OTS. This paper proposes an early warning model for OTS under long-term excessive training based on a stochastic probability distribution model, and constructs a regression analysis model for predicting the probability of athletes developing OTS in Sobolev spaces. The specific formula for the objective function to be controlled is:

$$\max_{x_{a,b,d,p}} \sum_{a \in A} \sum_{b \in B} \sum_{d \in D} \sum_{p \in P} x_{a,b,d,p} V_p \tag{2}$$

$$\text{s.t} \qquad \sum_{a \in A} \sum_{d \in D} \sum_{p \in P} x_{a,b,d,p} R_p^{dw} \le K_b^{bw}(S), b \in B \tag{3}$$

In a Banach space, the continuous function of the early warning model for the risk of OTS occurring under long-term excessive exercise is $u : I \times IR^d \to IR$, and the confidence level for the accuracy of the early warning of OTS under long-term excessive exercise is $c_1 e^{\lambda 1t} + c_2 e^{\lambda 2t} \left(\lambda_1 \ne \lambda_2\right)$ or $(c_1 + c_2 t) e^{\lambda t} (\lambda_1 = \lambda_2 = \lambda)$. In the regression analysis model, a correlation feature decomposition is performed on the sample sequence of the probability of OTS occurring under long-term excessive exercise, and the feature decomposition values of the regression analysis model satisfy:

$$f(x_1, x_2, i) - g(y_1, y_2, i) + \int (h(x_1, x_2, i) - g(y_1, y_2, i))xdu$$
$$< x(|x-y|^2 + x(|x+y|^2) \tag{4}$$

In this context, let $\forall x_1$, x_2, y_1, $y_2 \in R$, and x^* denote the weight contribution points in the vector solution set $\{x_k\}$ of the OTS early warning model for long-term excessive exercise. The OTS probability training vector model is as follows:

$$x(t) = (x_0(t), x_1(t), \ldots, x_{k-1}(t))^T \tag{5}$$

Using the BP algorithm for information fusion, a set of data generated from a series of randomly distributed features $N\left(m_k, \varepsilon_k^2\right)$ is used to construct a sequence of samples y_k for probabilistic analysis. The resulting Lyapunov exponent, which serves as the output for predicting the probability of OTS under long-term excessive exercise, is:

$$OTS = \frac{\sum_{i=1}^{TC} M_0(C_i)}{\sum_{i=1}^{TC} \left[M_n(C_i) \times DC(C_i)\right]} \tag{6}$$

$$M_d(C_i) = M_n(C_i) + M_0(C_i) \tag{7}$$

In the equation, $M_0(C_i)$ represents the steady-state vector model of the OTS probability for the BP algorithm structure under long-term overload operation, and $C_i (i = 1, 2, \ldots, n)$ represents the number of prediction inputs. Under long-term overload operation, the fusion scale of the OTS early warning model satisfies the Duhamel formula:

$$u(t) = \varpi(t)(u_0, u_1) + \int_0^t \frac{\sin(t-t')|\nabla|}{|\nabla|} F(u(t'))dt' \tag{8}$$

In this study, the scale invariance of the early warning for OTS under long-term excessive exercise is set to $F(u) = |u|^4 u$, and a boundary condition constraint method is employed to conduct a probabilistic experimental analysis of OTS under such conditions.

2.2.4. Feature Importance

Machine learning (ML) algorithms can also measure the importance of different features. Unlike the odds ratio (OR) in regression models, ML algorithms cannot provide a simple interpretable value because the relationships they fit are complex. Therefore, these relationships typically do not directly translate to any single parameter, nor do they imply causality or even offer a statistical interpretation. This measurement is generally viewed as a ranking of each variable's importance to the model fit. It serves as a method for generating hypotheses to identify factors requiring further investigation and provides insights into the factors with the greatest impact on predictions. Consequently, we utilized the algorithms provided by the R package "caret" to generate a feature importance ranking for the optimal ML predictive model.

2.2.5. Statistical Analysis Methods

The relevant data were processed using Excel 2021, and statistical analyses of the key indicators were further conducted using SPSS 21.0. Normal quantitative data are presented as mean ± standard deviation, while categorical variables are described using appropriate binary classification methods. Multivariate analysis of variance (ANOVA) was used to compare the main effects and interaction effects of different training methods, sampling time points, and exercise loads on OTS. Prior to conducting the ANOVA, Levene's test was used to assess the homogeneity of variances among the data.

After identifying the interaction effects among the factors, further simple effect tests are conducted. Analysis of variance is performed using the Bonferroni method. Experimental data that fail the homogeneity of variance test or are non-normal are transformed into LOG or square roots before statistical analysis. Regression analysis is used to further determine the relationship between OTS and objective indicators. If the linear regression fit is poor, nonlinear regression is used for processing.

Since multiple linear regression analysis involves multiple variables, severe multicollinearity problems can make model estimation inaccurate or even impossible. First, the problem of multicollinearity needs to be considered. The indicator used is the variance inflation factor (VIF). If VIF > 10, it indicates strong multicollinearity. Calculate R^2 to assess the impact of different indicators on OTS. R^2 Generally used in linear regression analysis, its range is 0-1, and the larger the value, the closer the predicted result is to the true value.

3. Results and Discussion

3.1. Description of the Basic Situation

The basic data are shown in Table 1. This database contains demographic data, training load data, athletes' subjective health perception data, physical fitness assessment data, and biochemical, hormonal, and immunological data for 72 adolescent elite athletes. The athletes' average age was 18.23 ± 2.25 years, average height was 177.56 ± 7.28 cm, average weight was 56.24 ± 5.35 kg, and average years of specialized training was 3.13 ± 0.84 years. The dataset comprised 1,905 records, with a data imbalance ratio of 10.7.

Table 1. Basic data situation

Variable	Mean ± SD	Min-Max
Age (Years)	18.23 ± 2.25	16.00-24.00
Height (cm)	177.56 ± 7.28	166.10-187.28
Weight (kg)	56.24 ± 5.35	46.22-82.63
BMI (kg/m^2)	20.89 ± 2.75	18.32-25.63
Specialized training duration (years)	3.13 ± 0.84	0.20-6.20
Training Load (TL, AU)	1.52 ± 0.62	0.00-4.30
Heart rate (HR, AU)	172.58 ± 13.28	159-182
The ratio of heart rate to RPE (HR/RPE, AU)	5.54 ± 1.28	3.00-7.86
Training Impulse (TRIMP, AU)	228.96 ± 34.86	108.18-258.80
Lactic acid concentration (LAC, AU)	6.83 ± 0.72	5.69-7.76
Heart rate recovery (HRR, AU)	29.34 ± 4.08	25.86-35.25
Heart rate variability (HRV, AU)	8.25 ± 2.70	6.80-8.90
Biochemistry, Hormones, Immunology (Others, AU)	0.67 ± 0.07	0.00-1.00

3.2. Variable Selection for Early Warning Models

Variables that showed marginal significance in the univariate analysis were included in the feature selection results, as shown in Figure 1. Compared with athletes at technical level 2, athletes at technical level 1 had a higher probability of OTS during the early warning period, and this result was statistically significant (OR = 4.238, 95% CI = 1.125–22.368, p = 0.031). Training load (TL) was positively correlated with the probability of OTS, and this result was statistically significant (OR = 1.168, 95% CI = 1.504–2.297, p = 0.008). Heart rate variability (HRV) was also positively correlated with the probability of OTS, and the result was marginally statistically significant (OR = 1.245, 95% CI = 1.106–1.254, p = 0.022).

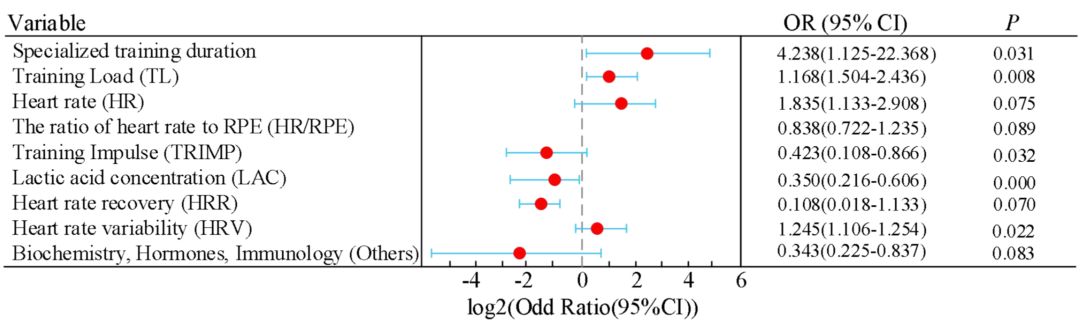

Figure 1. Inclusion Results of univariate analysis of variables

The aforementioned indicators for the athletes were standardized using Z-scores, and VIF was used to assess multicollinearity among the variables; the results are shown in Table 2. The results indicate that the VIF values for all variables were less than 10, suggesting that there is no multicollinearity among the variables.

Table 2. Results of Collinearity Diagnostic tests

Variable	Tolerance	VIF
Specialized training duration	0.636	1.660
Training Load (TL)	0.625	1.584
Heart rate (HR)	0.733	1.407
The ratio of heart rate to RPE (HR/RPE)	0.360	2.412
Training Impulse (TRIMP)	0.437	2.052
Lactic acid concentration (LAC)	0.211	3.825
Heart rate recovery (HRR)	0.385	1.446
Heart rate variability (HRV)	0.682	1.832
Biochemistry, Hormones, Immunology (Others)	0.280	2.052

3.3. Development and Performance Evaluation of the Early Warning Model

Based on the nine identified risk factors for OTS, we performed modeling using eight machine learning algorithms—RF, XGBoost, CatBoost, LightGBM, SVM, DT, GBC, and ANN—and compared the results with the Braden score. Table 3 compares the sensitivity, negative predictive value for OTS, specificity, positive predictive value for OTS, F1 score, AUC, and accuracy of the eight machine learning models, the logistic regression model, and the Braden score. Internal validation results showed that the LR model demonstrated the best performance, with an AUC of 0.841 (95% CI: 0.780–0.898) and an accuracy of 0.891 (95% CI: 0.882–0.918).

Table 3. Prediction performance of the model in the internal validation set

Model	AUC (95% CI)	Accuracy (95% CI)	Sensitivity	Specificity	F1
Braden score	0.723 (0.631-0.785)	0.861 (0.830-0.937)	1.000	0.000	0.918
LR	0.841(0.780-0.898)	0.891 (0.882-0.918)	0.989	0.181	0.945
CatBoost	0.832 (0.767-0.885)	0.882 (0.872-0.907)	0.995	0.113	0.935
XGBoost	0.811 (0.734-0.869)	0.874 (0.838-0.911)	0.986	0.147	0.934
RF	0.769 (0.685-0.821)	0.858 (0.843-0.904)	0.990	0.112	0.940
LightGBM	0.781 (0.709-0.855)	0.862 (0.834-0.901)	0.995	0.072	0.928
SVM	0.789 (0.729-0.845)	0.865 (0.823-0.893)	1.000	0.000	0.937
DT	0.652 (0.543-0.704)	0.856 (0.833-0.890)	0.981	0.082	0.917
GBC	0.820 (0.788-0.882)	0.878 (0.829-0.909)	0.998	0.080	0.932
ANN	0.727 (0.643-0.804)	0.872 (0.843-0.900)	0.965	0.168	0.935

Note: LR: Logistic Regression; CatBoost: Categorical Boosting; XGBoost: Extreme Gradient Boosting; RF: Random Forest; LightGBM: Light Gradient Boosting Machine; SVM: Support Vector Machine; DT: Decision Tree; GBC: Gradient Boosting Classifier; ANN: Artificial Neural Networks.

3.4. Model Validation and Clinical Utility

The calibration curve visually illustrates the model's predictive capability, as shown in Figure 2. The x-axis represents the risk threshold for OTS in athletes undergoing prolonged excessive training, while the y-axis represents the actual observed risk. The dashed line represents the ideal early warning model, while the solid line reflects the actual early warning performance of this model. The closer the solid line is to the dashed line, the better the model's early warning capability. In the internal validation, the high degree of overlap between the measured curve and the ideal curve further demonstrates that the model's early warning effectiveness is reliable and that the prediction results are consistent with actual conditions. The Brier score of 0.081 further validates the model's excellent early warning accuracy.

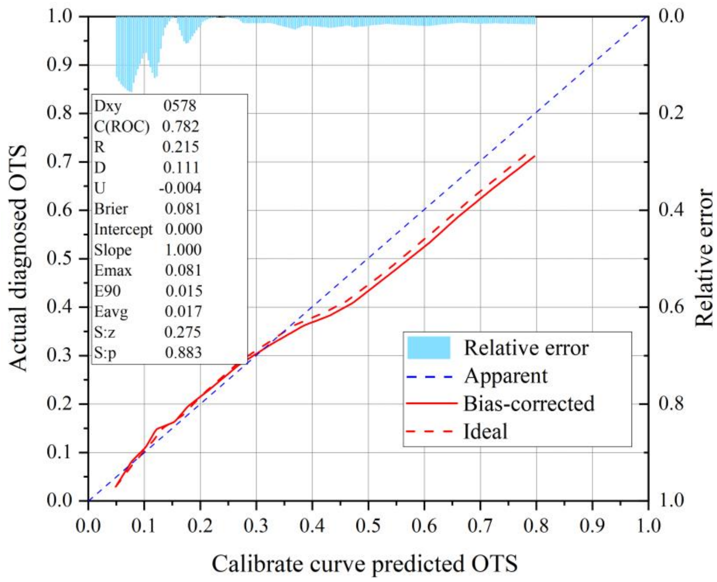

Figure 2. Model Calibration Curve

Figure 3 presents the results of the decision curve analysis for the OTS early warning model. The Y-axis represents net benefit, while the X-axis represents the high-risk threshold. The blue solid line (None) assumes that none of the athletes develop OTS under long-term excessive training, while the blue dashed line (All) assumes that all athletes develop OTS under long-term excessive training (a universal intervention strategy). The red curve shows the performance of the model developed in this study on the validation set. As shown by the decision curve, when the threshold probability is set between 0% and 75%, the net benefit of the OTS early warning model exceeds that of the universal intervention or no-intervention strategies within this range, suggesting its potential for clinical application. This indicates that within this probability range, the model can effectively guide clinical decision-making, helping to optimize intervention measures, reduce unnecessary treatment burdens, and ensure that high-risk OTS patients receive timely management.

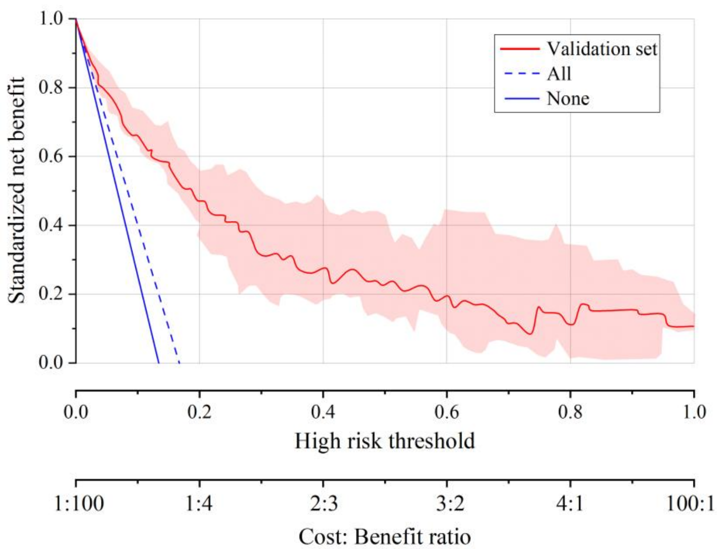

Figure 3. Decision curve of the OTS early warning model

4. Discussion

In this study, we developed and evaluated nine predictive models based on eight clinical variables collected within 24 hours of hospital admission to assess their ability to provide early warning for OTS. Among these models, the logistic regression model performed best. This optimal model incorporated two key variables—training load (TL) and heart rate variability (HRV)—and demonstrated high net benefit and good calibration. These results suggest that the model has the potential to help clinicians identify high-risk OTS patients early, thereby enabling timely intervention and ultimately improving patient outcomes.

It is worth noting that this study found that logistic regression models significantly outperformed the Braden score in predicting the onset of OTS in athletes undergoing prolonged excessive training; however, the Braden score remains an important independent predictor of OTS onset and demonstrated a statistically significant correlation. Although the Braden score is an important tool for assessing the risk of OTS onset, its predictive ability may have certain limitations in specific patient populations and clinical settings. In this study, the Braden score demonstrated high sensitivity, consistent with the 83%–100% range reported in previous studies. However, this high sensitivity may be accompanied by low specificity, meaning the Braden score is prone to misclassifying low-risk OTS patients as high-risk, resulting in a high false-positive rate. This may not only increase the workload of healthcare providers but also lead to inefficient allocation of nursing resources. Previous studies evaluating the subscales of the Braden score have found that only persistent weight loss, lack of improvement in exercise performance, and the onset of left-sided rib pain are significantly associated with the occurrence of OTS in patients undergoing prolonged excessive exercise. Furthermore, existing reviews have categorized risk factors for OTS in critically ill patients into aspects such as functional capacity/mobility, physical condition, overall health status, and hematological indicators, suggesting that the pathogenesis of OTS may be more complex. Under conditions of prolonged excessive exercise, traditional assessment scales have clear limitations and require integration with more precise and individualized evaluations. Therefore, this study developed an early warning model for OTS in patients undergoing prolonged excessive exercise by integrating the traditional Braden score with other key clinical factors. This model provides clinical healthcare professionals with a more accurate early risk assessment for OTS and serves as a basis for timely intervention and adjustments to care.

This study found that heart rate variability and exercise intensity are the most significant risk factors for OTS. OTS is one of the most common conditions affecting athletes and individuals who engage in regular physical activity. According to published survey results, more than 50% of long-distance runners will be affected by this condition during their athletic careers, and more than half of professional athletes will develop it approximately five months before or after a competition. However, there is currently no universally accepted, clear definition of this condition, nor are there practical diagnostic tests available, and its underlying pathophysiology remains unclear. Although carefully designed programs specifically aimed at preventing OTS are introduced every year, even the most experienced coaches cannot predict which athletes will experience a decline in performance—the sole common symptom of this condition. The condition goes by many different names, such as fatigue, chronic fatigue, overtraining, and physical exhaustion. OTS generally manifests as a decline in athletic performance following high-intensity training, accompanied by symptoms such as generalized fatigue, malaise, decreased energy, insomnia, changes in appetite, irritability, restlessness, agitation, anxiety, weight loss, reduced motivation, impaired concentration, feelings of depression, poor heart rate recovery, persistent fatigue, and decreased muscle strength. Certain changes are also observed in blood biochemistry. The results of this study indicate that monitoring various indicators is highly significant for preventing OTS; however, a single indicator cannot achieve the goal of accurate monitoring. The currently accepted method for diagnosing OTS involves monitoring physical performance at rest over a period of several days or weeks. However, this approach is not accepted by coaches and athletes because it may disrupt the periodicity and continuity of training. Therefore, early diagnosis of OTS using machine learning models can reduce the occurrence of its adverse effects.

5. Conclusion

This paper proposes an early warning model for OTS under long-term excessive training, based on random probability distributions and machine learning algorithms. A total of eight potential influencing variables were identified: training load, heart rate, the ratio of heart rate to RPE, training volume, lactate concentration, heart rate recovery, heart rate variability, as well as biochemical, hormonal, and immunological parameters. Currently, the established model demonstrates good performance and exhibits strong predictive capability in external validation (AUC ranging from 0.652 to 0.841). Furthermore, the model shows significant clinical utility in terms of calibration and decision analysis.

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