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*Research Article*

# Maximal Oxygen Uptake in Breathing Exercises and Heart Rate Exercises Based on In-Depth Regression Equations

**Jinchan Min**

*Shaanxi Xueqian Normal University, Xi'an 710100, Shaanxi, China*

Correspondence should be addressed to Jinchan Min; 1431105129@post.usts.edu.cn

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For the purpose of research, the maximum oxygen uptake of exercise training breathing and heart rate constructed based on the deep learning regression equation learn about the effects of training breathing and heart rate on VO2 max. Based on 77 healthy adults without chronic diseases (37 men and 40 women, aged 20–39 years old), who participate in two exercise tests (the first time is a direct test and the second time is a secondary quantitative load plan), in order to establish a second-level quantitative load scheme for power vehicles, the predictive equation for predicting the maximum oxygen uptake. The author researched and established a stable heart rate HRH based on gender, BMI, and second-level load; the second-level load RPE and $RPE_1$ are independent variables, the absolute value of the subject's maximum oxygen uptake is the regression equation of the dependent variable. The experimental results prove that the reliability and validity of the second-level quantitative load scheme for power vehicles are better and can be used as the maximum oxygen uptake in the laboratory, directly tested with alternative submaximal solutions, and used for large-scale investigation of maximum oxygen uptake data. At the same time, since the load is submaximal, it can also be used to clinically assess the patient's cardiorespiratory endurance.

## 1. Introduction

Heart rate is an important vital sign; it is one of the most direct and effective indicators to assess physical condition. When the human blood volume and metabolism are basically unchanged, the change in heart rate directly reflects the functional state of the heart and can reflect the working conditions of the heart in various states; research shows that the resting heart rate is too fast, which is more likely to cause cardiovascular disease [1]. In addition, due to the state of exercise, It is easy to cause heart rate changes, abnormal heart work; the heart rate also plays an important role in the assessment of exercise status. Therefore, heart rate monitoring is of great significance to disease prevention and sports health. Normally, collect the pulse signal, which is easy to be disturbed by human activities and the outside world; it is difficult to accurately obtain dynamic heart rate information [2]. Heart rate measuring equipment is often caused by severe noise; this leads to problems such as large errors in the measured values of equipment and false warnings. The maximum oxygen uptake is in the cardiopulmonary function and the organs of the body, under the condition that the system is fully mobilized, in unit time, the amount of oxygen absorbed and used by the body. Maximum oxygen uptake (VOmax) is the most direct and effective indicator for assessing aerobic work capacity. It reflects the maximum capacity of the human body to consume oxygen during exertion. It can be divided into absolute maximum oxygen uptake and relative maximum oxygen uptake [3]. The absolute value unit is expressed as L/min, and the relative value unit is expressed as mL/(kg ∗ min). Factors that affect the maximum oxygen uptake is mainly determined by the oxygen transport capacity and the oxygen uptake capacity of peripheral tissues. After exercise under the same exercise load, heart rate recovery is often used as a reference data for observing athletes' exercise status; the principle is the recovery speed of heart rate after exercise, reflecting the athlete's aerobic capacity, but there is no research to confirm the recovery of heart rate after exercise, correlation with maximal oxygen uptake. This research adopts an experimental method, explores the correlation between heart rate recovery and maximal oxygen

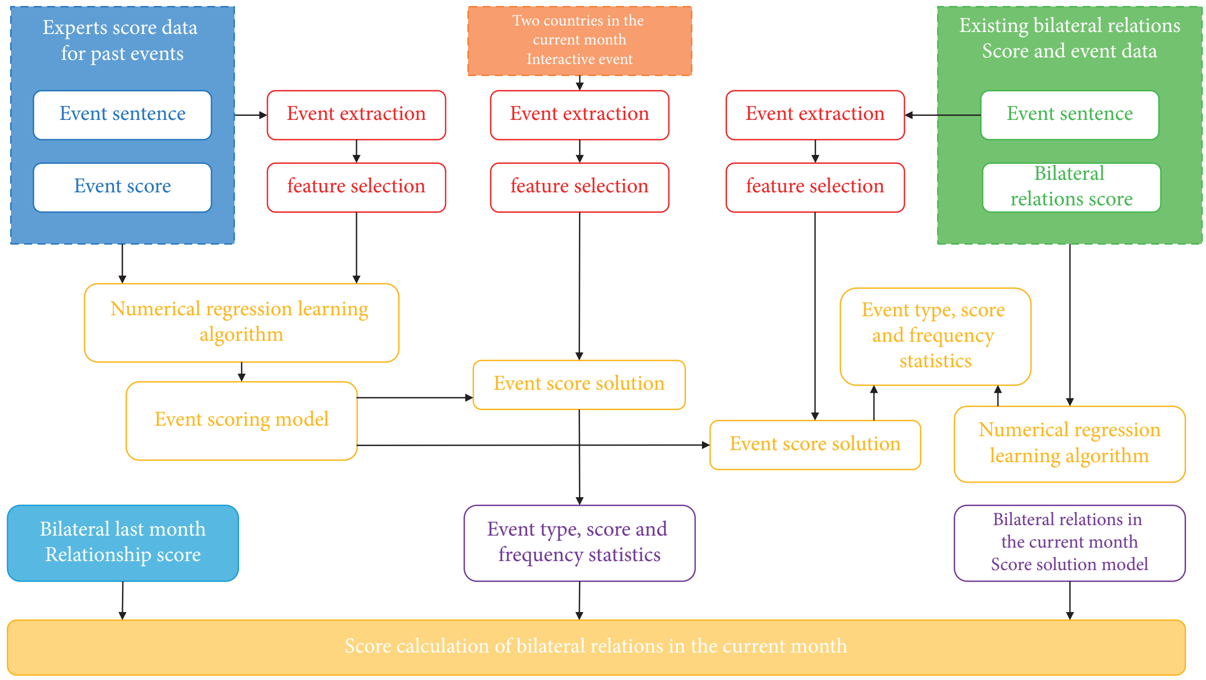


FIGURE 1: Linear regression equation.

uptake after exercise, and establishes the prediction equation through regression analysis (Figure 1).

## 2. Literature Review

Richter. A et al. , in 2006, based on sample data, through certain training methods, obtained the machine learning process with multiple levels of deep network structure [4]. When Armstrong and Welsman were studying dual-channel pulse sensors, according to the physiological and anatomical characteristics of the human wrist, they proposed a dual-channel pulse of the radial artery and ulnar artery, and a method for synchronous detection of differential signals has a certain anti-interference ability for slight movements; the detection method was verified through experiments, but the heart rate detection module is too large and cannot be in the state of running, etc., and makes an accurate estimate of the heart rate [5]. When Jaime et al. studied the method of multisensor fusion, fusion of ECG, and pulse wave signals to obtain fusion heart rate, compared with the heart rate obtained from ECG or pulse signal alone, the accuracy of the fusion heart rate is increased by more than 46%, but this method is not very wearable, and only within the prohibition and normal movement range can the interference be effectively avoided [6]. When Gielen et al. studied the use of adaptive filters, used a three-axis accelerometer to get the noise source and constructed an adaptive filter to eliminate equipment motion interference, which can be used for daily health maintenance; however, the measurement accuracy of the motion state needs further improvement [7]. Sipil et al. studied noncontact heart rate monitoring, by analyzing the changes in the light intensity of the blood and tissues of the face, derived the periodic changes of these light components, and quantitatively obtained the periodic signal changes of the pulse and the accuracy of this method, affected by filtering algorithm and camera frame rate [8]. Hanson et al. developed a binary regression prediction equation for the actual measured maximum oxygen uptake and can better reflect the actual maximum oxygen uptake. The maximum oxygen uptake is an important index to evaluate the aerobic work capacity of the human body. There are also people whose heart rate stabilizes at 170 beats/min, and the attained power estimates the maximum oxygen uptake [9]. Wataru proposed to predict the ratio of the maximum heart rate to the resting heart rate; in order to guess the maximum oxygen uptake and its measured maximum heart rate and resting heart rate, it uses the measurement during the exercise experiment; its accuracy is yet to be determined [10]. Vitor pointed out that the initial increase in the motor center rate was caused by the decrease in parasympathetic tone, and at high load, the increase in heart rate is caused by the sympathetic nervous system, which stimulates the sinoatrial and atrioventricular nodes [11]. Ulrich et al. believe that the nervous and endocrine systems, regulate cardiovascular function, and are the cause of the rapid drop in the heart rate in the early recovery period after exercise; it is also an important manifestation of exercise-induced heart function adaptation. The slow recovery of the heart rate decline depends in part on the exercise load [12]. Judy believe that, although the direct measurement of VO2max is a golden method, however, due to problems and disputes in various aspects, for epidemiological studies of large samples, the submaximal program infers that the maximum oxygen uptake has been sufficiently effective and reliable [13]. Although the results of the indirect determination method are not very accurate, it requires less equipment, simple operation, and low detection cost. Therefore, many researchers have been looking for a simple, convenient, and effective

Table 1: Basic situation of the sample of exercise plan.

| | Sample size (person) | Height (cm) | Weight (kg) | BMI |
|---|---|---|---|---|
| Man | 95 | 172.3 ± 12.5 | 72.3 ± 10.54 | 25.6 ± 2.18 |
| Woman | 96 | 162.3 ± 9.23 | 55.2 ± 8.67 | 23.5 ± 3.98 |
| Total | 191 | | | |

Table 2: The basic situation of the sample for formulating the prediction equation.

| | Sample size (person) | Height (cm) | Weight (kg) | BMI |
|---|---|---|---|---|
| Man | 37 | 170.8 ± 11.6 | 75.3 ± 6.54 | 24.3 ± 3.28 |
| Woman | 40 | 163.5 ± 8.23 | 54.2 ± 9.23 | 21.5 ± 2.31 |
| Total | 77 | | | |

method to indirectly test VOmax with high accuracy. Especially, in the measurement and evaluation of college students' physical fitness, VOmax has not been widely used.

## 3. Experimental Methods and Results

*3.1. Subjects.* Eight physiological indicators of age, height, weight, BMI, vital capacity, and immediate heart rate, resting heart rate, and measured VOmax absolute value of male and female students were clustered and analyzed, and the indicators in the same category as the measured VOmax absolute value were the immediate heart rate and vital capacity of the steps are the most similar to the measured values: weight, height, and BMI. All healthy adults between the ages of 20 and 39 are subjects; they are the research objects of the exercise program of the second-level quantitative load program of the power car, no chronic diseases, all have completed the direct test of maximal oxygen uptake, as shown in Table 1.

All healthy adults aged 20–39 are subjects; they are the research objects of the second-level quantitative load forecasting equations for power vehicles, no chronic diseases, and all have been screened by the PAR-Q questionnaire and signed the informed consent form for the exercise test, as shown in Table 2.

*3.2. Research Methods*

*3.2.1. The Development Method of the Two-Stage Quantitative Load Plan of the Power Car.* Two-level quantitative load plan is based on the linear relationship between human oxygen uptake and heart rate (or workload), developed with the principle of operability. The linear relationship between human oxygen uptake and heart rate (or workload) is the theoretical basis of all submaximal programs. This refers to the oxygen uptake, as the heart rate (or workload) increases and linear increases. However, many scholars have proposed that this linear relationship is only established within a limited range. And the traditional submaximal scheme, such as A-R plan (hereinafter referred to as AR plan) and YMCA plan, all are based on this linear relationship. If the load intensity is too low, the part of the nonlinear relationship between oxygen uptake and heart rate will not be taken into account; as a result, the formula is inaccurate in the estimation of the maximum oxygen uptake [14]. Based on the above considerations, the author will try to determine the physiological burden of the secondary quantitative negative He Wan case, combined with the large sample population accumulated in the previous period; the maximum oxygen uptake data calculation gets the actual load intensity of the plan and divides the program movement phases; the purpose is to allow the body to enter the state of exercise as soon as possible and ensure the stability and effectiveness of the test parameters.

Table 3: Exercise programs used in the direct test of VO2max in this study.

| Generation | Initial load | Incremental load | Duration of each level (min) |
|---|---|---|---|
| Man | 24 w | 26 w | 4 |
| Woman | 0 w | 30 w | 4 |

*3.2.2. The Development Method of the Second-Stage Quantitative Load Scheme Forecasting Equation for Power Vehicles.* The exercise mode of the test plan keeps the riding speed at 60 rpm throughout the entire journey; they are all riding Custo Med power bikes wearing Cortex Metalyze 3B cardiopulmonary function tester and matching mask and a polar heart rate monitor and blood pressure belt, which are used to monitor heart rate and blood pressure during exercise. The specific plan is shown in Table 3.

Since the maximum oxygen uptake incremental load test is an extreme test, we ask the subject to exercise to the limit; therefore, it has a higher risk of exercise [15]. This study mainly uses blood pressure (blood pressure test is performed every two minutes) and self-inspection (in the form of questioning by the tester and self-reporting by the subject) to carry out exercise risk monitoring. If, during the test, the subject's systolic blood pressure exceeded 220 mmHg or diastolic blood pressure decreased and the subject feels dizzy, palpitation, and nausea, stop the test immediately to ensure the safety of the test.

After 24 h or 48 h, subjects participate in the exercise test of several levels of quantitative load schemes for power vehicles, and we ensure that subjects have enough time to rest and recover, in order to prevent test interference caused by fatigue. In addition, for some subjects (50 people), when participating in the second test, in addition to wearing a heart rate monitor, they also wear the same gas metabolism analyzer as the first test, which is used to extract gas metabolism data in the secondary quantitative load scheme of power vehicles, and analyze changes in gas metabolism.

Suppose $Y = F(X, U)$ is a regression model, where $Y$ is income or a transformation of the income variable (such as log transformation), $X$ is the factors affecting income or their proxy variables, and $U$ is the residual term. Assuming that there is a constant term in the regression model, $Y$ can be expressed as

$$Y = \alpha + Y + U, \tag{1}$$

where $Y = \alpha + U$ is the deterministic part of the model and $Y$ represents the income stream generated by different variables. If $F(X, U)$ is linear, $Y = \sum \beta_i X_i = \sum Y_i$, where $Y_i = \beta_i X_i$ represents the income stream generated by the $i$ factor. For ease of description, we use the Gini coefficient as a measure of

$$Y = OI = \alpha + \sum_i Y_i + U. \tag{2}$$

In $Yi = \beta_i X_i$ and $Y = \alpha + \sum Y_i$, applying the Gini index $G$ to both sides of equation (2) according to the MS method, we can obtain

$$G(Y) = 0 + \sum_i \frac{E(Y_i)}{E(Y)C(Y_i)} + 0. \tag{3}$$

To derive the contribution of factors or random terms not included in the model, we use Shorrocks' method to remove $U$ from (2) to obtain

$$Y(U = 0) = Y. \tag{4}$$

And we get $G(YU = 0) = G(Y)$. In this way, the contribution of $U$ to $G(Y)$ can be defined as

$$CO_u = G(Y) - G(Y). \tag{5}$$

In (4), the difference between $Y$ and $Y^\wedge$ can be completely attributed to $U$. When $U$ tends to 0, $G(Y)$ tends to $G(Y^\wedge)$, and $G(Y) - G(Y^\wedge)$ tends to $U$ at the same time. Therefore, it is reasonable to attribute $Y$ to the contribution of $Y^\wedge$. Although the expected values of $G(Y)$ and $G(Y^\wedge)$ are the same, we can express the sum as

$$G(Y) = \sum_i \frac{E(Yi)}{E(Y)C(Yi)}\Big|_{\text{rakby}Y}, \tag{6}$$

$$G(Y^\wedge) = \sum_i \frac{E(Yi)}{E(Y)C(Yi)}\Big|_{\text{rakby}Y^\wedge}. \tag{7}$$

From formula (4), it can be known that

$$G(Y) = G(Y^\wedge) + CO_u. \tag{8}$$

From this, the contribution of the constant term can be defined as

$$CO_\alpha = G(Y) - G(Y^\wedge). \tag{9}$$

Obviously, if $\alpha > 0$, then $CO_\alpha > 0$ , and vice versa. The resulting change in inequality can be attributed to $\alpha$ contribution. Following this reasoning, we have

$$CO_\alpha = \sum_i (W_i - W_i) C(Y_i) = G(Y) - G(Y^\wedge). \tag{10}$$

*3.3. Experimental Results.* Two-level quantitative load plan is essentially a simplified version of incremental load testing. Many scholars have confirmed that, during the incremental load test, as the work intensity increases step by step, oxygen uptake and heart rate also increase linearly; there is a definite regularity [16]. In the incremental load test used by the author, the same pattern appears between oxygen uptake, heart rate, and workload, and the change curve is shown in Figure 2.

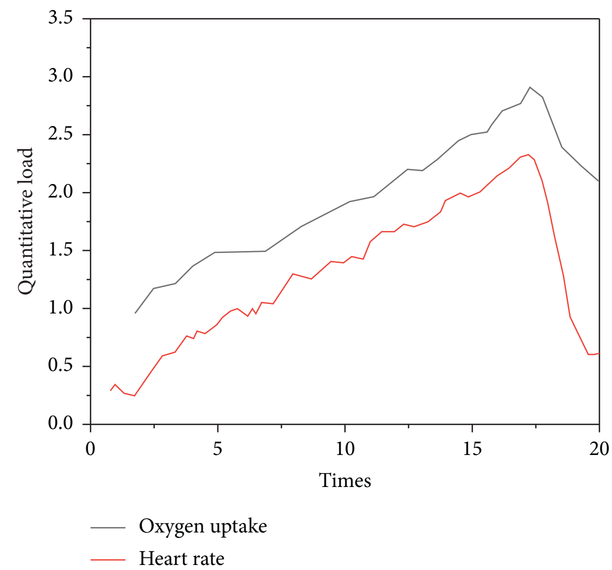


Figure 2: The change curve of oxygen uptake, heart rate, and workload in the incremental load test.

As can be seen from Figure 2, as the load increases, oxygen uptake and heart rate increase at the same time, and the changes of the two are almost synchronized and have a high correlation [17]. In the test, at each load stage, both the oxygen uptake curve and the heart rate curve have a higher slope and then gradually calm down; at lower intensities, there is a clear oxygen uptake plateau or heart rate plateau; then, the slope increases again to adapt to the next higher load stage. This "adaptation/nonadaptation" law of change laid a foundation for the changes in the central lung function of the secondary quantitative load plan.

Table 4 shows the correlation coefficient of the two-level quantitative load scheme. $HR_1$ and $HR_2$ are the stable heart rates in the first load stage and the second load stage, respectively. $RPE_1$ and $RPE_2$ are RPE in the first load stage and the second load stage, respectively. Absolute$VO_{2max}$ is through the maximum oxygen uptake; the actual value (absolute value) of the maximum oxygen uptake is obtained by the direct test.

The test parameters of the second-level quantitative load scheme of the power car are the subject's gender, BMI, age, and first-level load heart rate (at the end of the 2nd minute, at the end of the 2nd minute and a half, and at the end of the 3rd minute stabilize the heart rate); the first-level load is RPE; the second-level load stabilizes the heart rate (at the end of the 2nd minute, at the end of the 2nd and a half minutes, and at the end of the 3rd minute; the heart rate is stabilized), and the second-level load is RPE[18]. Choosing from them has theoretical significance and statistically significant indicators, in order to the maximum oxygen uptake prediction equation.

Table 4: Basic results of the secondary quantitative load plan test.

| Gender | Age group | $HR_1$ | $HR_2$ | $RPE_1$ | $RPE_2$ | Absolute$VO_{2max}$ |
|---|---|---|---|---|---|---|
| Male | 20–39 | $120.5 \pm 12.6$ | $153.5 \pm 12.6$ | $8.3 \pm 2.3$ | $12.6 \pm 3.2$ | $2.536 \pm 0.231$ |
| Female | 20–39 | $125.1 \pm 11.3$ | $161.1 \pm 8.3$ | $10.3 \pm 2.6$ | $13.1 \pm 1.9$ | $1.564 \pm 0.154$ |

Table 5: Comparison of plan peak oxygen uptake and maximum oxygen uptake.

| | Mean value (L/min) | Standard deviation (L/min) |
|---|---|---|
| Protocol peak oxygen uptake | 1.539 | 0.421 |
| Maximal oxygen uptake | 1.852 | 0.529 |

In addition, the percentage of peak oxygen uptake to maximum oxygen uptake in the plan is calculated, as shown in Table 5. Use this to measure the strength of the program. The average of this percentage is 82.2%; we meet the requirement of 80% $VO_{2\,max}$ for the second-level load at the beginning of the scheme design and lay the foundation for the reliability and validity of the program forecast. At the same time, the percentage of each subject indicates the current exercise load and the physiological load on the subject; it also represents the subject's aerobic capacity to a certain extent [19]. The finally calculated Spearman correlation coefficient is −0.76, $\alpha < 0.01$, explain the exercise load of the plan; it can effectively represent the subject's aerobic capacity, which further proves the validity of this program.

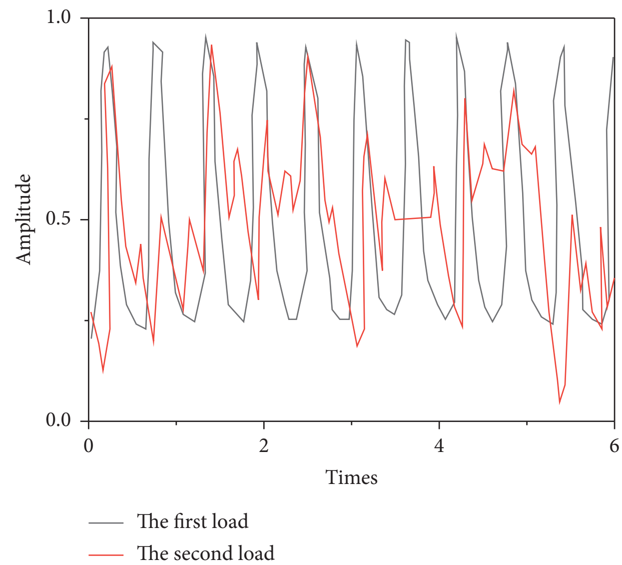


Figure 3: Load quantification and equation forecasting.

## 4. Discussion

*4.1. Deep Learning.* Deep learning is based on sample data; through certain training methods, we obtain a machine learning process with multiple levels of deep network structure. A deep neural network is composed of multiple single-layer neural networks, and common single-layer neural networks are divided into 3 categories according to the coding situation: contains only the encoder part and only the decoder part; the encoder provides a bottom-up mapping from the input to the hidden feature space and the decoder to reconstruct the result, as close as possible to the original input as the goal; the implicit feature map is input into the space [20, 21]. Deep neural networks are divided into the following 3 categories: (1) the feedforward deep network is formed by superimposing multiple encoder layers; (2) the feedback deep network is composed of multiple decoder layers superimposed; (3) bidirectional deep network is constructed by superimposing multiple encoder layers and decoder layers. The difference between deep learning and traditional shallow learning is that when deep learning builds a network model, it contains multiple hidden layers and generally contains 3–10 hidden layers. The hidden layer can have fewer nodes than the input layer, which forces the network to learn more effective features; it can also be more than the input layer, which is equivalent to converting the signal to a new coordinate space representation; this will make the final fitting and classification more accurate [22].

*4.2. Theoretical Meaning of the Regression Equation.* The independent variables of the prediction equation in this case include gender, BMI, heart rate, and RPE during the second load phase. Gender is an important factor influencing VO2 max, due to physiological differences between men and women; the difference in maximum oxygen uptake is also significant. Although the load schemes of men and women are not the same (male: 70 w–140 w; female: 50 w–100 w), but their physiological load is both 40% and 80% $VO_{2\,max}$; therefore, based on the principle of simplicity and ease of implementation, we put gender as an important predictor variable into the prediction equation, instead of establishing an equation for males and females separately [23]. Figure 3 shows that it can be seen from the above statistical results that if the relative value of the maximum oxygen uptake is used as the predictive dependent variable, not only will it lead to a decrease in the validity of the prediction but also it will lead to an important predictive independent variable; heart rate cannot enter the predictive equation, and the original purpose of the prediction is not achieved. There are also several reasons; as a result, the relative value is not suitable as a predictive dependent variable:

(1) The oxygen uptake value measured by the gas metabolism analyzer is an absolute value, which is the absolute amount of oxygen intake. Therefore, when forecasting oxygen uptake, the absolute value should also be used for forecasting. If the relative value is the target, the predictive significance is questioned.

(2) The relative value is to exclude the interference of body weight on oxygen uptake, but according to the above statistical analysis, although the relative value has been used as the dependent variable, BMI still enters the prediction equation as a strongly correlated independent variable, which is contrary to the theoretical significance of prediction [24]. Therefore, from a statistical point of view, the relative value is not suitable as a dependent variable.

## 5. Conclusion

By comparing the respiration rate tested by these two methods, the correlation with the heart rate index is obtained. The results of the indicators measured by the two methods had a certain correlation ($r = 0.85$, $P < 0.01$) and the maximum oxygen uptake was placed in the relevant altitude, age, gender, measured static indicators, resting heart rate, and exhaustion. For indicators such as heart rate, maximum heart rate, and respiratory rate in the planned load, correlation analysis shows that the maximum oxygen uptake is selected as the dependent variable, and gender, age, height, weight, body mass index, exhaustive heart rate, maximum heart rate, and respiratory rate are selected as independent variables, and perform a stepwise regression analysis on the results. Among these indicators, gender, weight, body mass index, maximum heart rate, and respiratory rate are five indicators which enter the regression equation. The author developed a two-level quantitative load plan for power vehicles, through heart rate, RPE, in order to predict the prediction equation of maximum oxygen uptake, high reliability, and validity after testing, can be used for large-scale cardiorespiratory endurance research and can conduct relevant epidemiological studies. Today, VOmax is not only used in the exercise physiology laboratory to evaluate the motor function limit of the cardiovascular system and a commonly used index of cardiac and health status but also clinically used to evaluate the patient's status, the effect of rehabilitation treatment, and the selection of cardiopulmonary transplantation cases. It can be used as a reliable parameter for patients' maximum exercise tolerance [25].

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The author declares no conflicts of interest.

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