SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2025, 22(3), 606.
https://doi.org/10.62617/mcb606

Article

Biomechanical and biochemical indexes of sprinters during training based on health monitoring: A Mechanobiological perspective

Wenzhi Hou, Pingyang Wang*

Institute of Physical Education, Xingyi Normal University for Nationalities, Xingyi 562400, China
*** Corresponding author:** Pingyang Wang, houwenzhiswimming@163.com

CITATION

Hou W, Wang P. Biomechanical and biochemical indexes of sprinters during training based on health monitoring: A Mechanobiological perspective. Molecular & Cellular Biomechanics. 2025; 22(3): 606. https://doi.org/10.62617/mcb606

ARTICLE INFO

Received: 24 October 2024
Accepted: 26 November 2024
Available online: 17 February 2025

Abstract: To promote and strengthen the scientific nature of sprint training, this study investigates the interplay between biochemical indicators and biomechanical responses during athlete training using a Zigbee-based health monitoring system. This system conducts real-time health monitoring of sprinters. The system uses sensors to collect human physiological signals and transmits them to the monitoring center through wired or wireless methods. The human motion recognition algorithm is used to establish a state space model of human body acceleration, and dynamic modeling methods and Kalman filtering for precise estimation and analysis of the athlete's biomechanical state. significant differences in the biochemical indicators of sprinters at different training stages, highlighting how these changes correlate with biomechanical responses such as force production, joint angles, and movement patterns. This research underscores the importance of integrating biomechanical assessments with biochemical monitoring to provide a comprehensive understanding of athletes' physiological status and optimize training regimens. The insights gained from this study contribute to the fields of biomechanics and mechanobiology, offering valuable implications for improving athletic performance and health monitoring.

Keywords: biomechanics; health check; sprinter training; biochemical index; physical training; mechanobiology

1. Introduction

Speed races are cyclical sports with the shortest distance, the highest exercise rate, and the lowest and greatest strength of the body in a state of anaerobic metabolism. Therefore, the top speed is an important determinant of the performance of various sports in the racing competition. As the main event of extreme-intensity exercise is headed by the ability to supply proto-nutrient phosphate, since proto-phosphate cannot adapt to its exercise requirements in terms of energy, glycogen also needs to participate in the supply of heat energy. The anaerobic nutrient supply and the mixed supply of anaerobic and aerobic energy are the physiological basis of racing. Therefore, anaerobic nutrient supply and the ability to supply anaerobic and aerobic mixed nutrients are the cornerstones of the improvement of racing performance. The exercise load and load intensity are the most basic factors to determine the effectiveness of exercise, and the speed of movement and rapid strength can be used as the most important special qualities to determine the exercise results of racing athletes. At present, although many scholars have made further innovative developments in the research of sprint training, they still need to keep in-depth exploration.

Currently, physiological and biochemical indicators and their application in sports training have become relatively popular research topics in China. With the advancement of science and technology, health monitoring technology plays an increasingly important role in tracking athletes' physiological and biochemical indicators. The research is based on health monitoring and aims to analyze the biochemical indicators of sprinters during training, explore the application of ZigBee technology in health monitoring, and analyze the changes in the levels of certain blood biochemical indicators of athletes at different training stages, to promote and strengthen sprint training. Scientific and practical advice is provided. The study finds significant differences in the biochemical parameters of sprinters during different training stages.

The innovations of this article are: first, the study introduces a health monitoring system based on ZigBee for real-time monitoring of sprinters. This system combines the advantages of wired and wireless transmission technologies to achieve real-time performance and flexibility of data and provides athletes with health monitoring, and new technical means. Second, the study adopts the human movement recognition algorithm and Kalman filtering method to improve the fitting accuracy of human body state change trends and provide a scientific basis for accurately evaluating the training effects of athletes. Finally, by comparatively analyzing the changes in biochemical indicators of sprinters at different stages, the study reveals the profound impact of training intensity on the physiological status of athletes, providing theoretical support for the development of more scientific and reasonable training plans.

2. Related work

Judging from the research progress at home and abroad, different scholars have also cooperated to a certain extent in health testing and sprinter training. Yt A used the frequency analysis method (FAM) to study the muscle fatigue and recovery of male sprinters and evaluated the interference current (IC), maximum voluntary contraction (MVC), and surface electromyography (EMG) amplitude of different sensory, motor and pain response thresholds before and after acute explosive fatigue training. Studies have shown that changes in IC precede changes in EMG and strength during fatigue, and these changes may reflect changes in physiological sensations caused by peripheral fatigue. FAM can be used as an effective early detection and simple tool for monitoring muscle fatigue during athlete training and recovery [1]. Miyake Y used magnetic resonance imaging to measure the quadriceps CSA and knee extensor MA of well-trained male sprinters and male non-sprinters. Studies have shown that the knee extensor MA of sprinters is greater than that of non-sprinters, and this morphological structure of sprinters is related to sprint performance [2]. Reeta K's study measured the levels of inflammatory and apoptotic molecules in the serum of male athletes undergoing sprint training, their changes over 10 years, and their relationship with physical performance. The results showed that changes in serum molecules were age-related and associated with a decline in physical function. They may serve as biomarkers of aging-related processes that affect the development of physiological dysfunction [3].

Studies have shown that athletic performance is affected by external forces and bone density. Chtourou H aimed to study the effects of listening to music during the warm-up period on Wingate test scores, rate of perceived exertion (RPE), and mood in sprinters and long-distance runners. The results showed that listening to music could improve the short-term maximum performance of sprinters. However, music had no significant effect on the performance of long-distance runners [4]. Kopiczko A's study aimed to evaluate the correlation between bone density and bone mass with physical activity levels, vitamin D, phosphorus, magnesium, total cholesterol, and triglyceride concentrations, and body. The conclusions showed that physical activity had the most significant effect on bone status, especially in men [5].

When monitoring exercise, the use of cloud computing and related intelligent algorithms is a good choice. Verma P proposed remote patient health monitoring in smart homes using the concept of cloud computing on smart gateways. The proposed model used advanced technologies and services such as embedded data mining, distributed storage, and notification services at the edge of the network. The results showed that decision-making based on real-time healthcare data further enhanced the practicality of the proposed system [6]. The main purpose of Padmavathy T V is to study the feasibility of using circular and rectangular slot microstrip patch antennas as strain sensors for structural health monitoring. The simulation results of these antenna sensors (rectangular and circular microstrip slot antennas) have been confirmed. According to the simulation results, the sensors can provide information about the crack direction [7]. However, these scholars did not analyze or discuss the biochemical indicators of sprinters during training from the perspective of health monitoring but only explored its significance one-sidedly.

3. Methods of biochemical indicators of sprinters during training based on health monitoring

3.1. Health monitoring system based on Zigbee

The health monitoring system is a system for real-time monitoring of human health. It collects human physiological signals through sensors, and then transmits these physiological data to the monitoring center in a wired or wireless manner so that the monitoring center can monitor human health in real time. This system can not only increase the safety of patients and the elderly and improve people's quality of life but also prevent some common diseases [8].

The health monitoring system has two transmission technologies: wired and wireless. Most of the original health monitoring systems use wired networks to monitor patients in the hospital. In this way, the line is connected to the human body for monitoring, causing psychological barriers to patients, especially patients in the ward. The complicated connection system not only makes the patient feel very uncomfortable, but also makes the whole ward chaotic, and even affects the work efficiency of medical staff [9]. **Figure 1** shows a health network system based on human body communication.

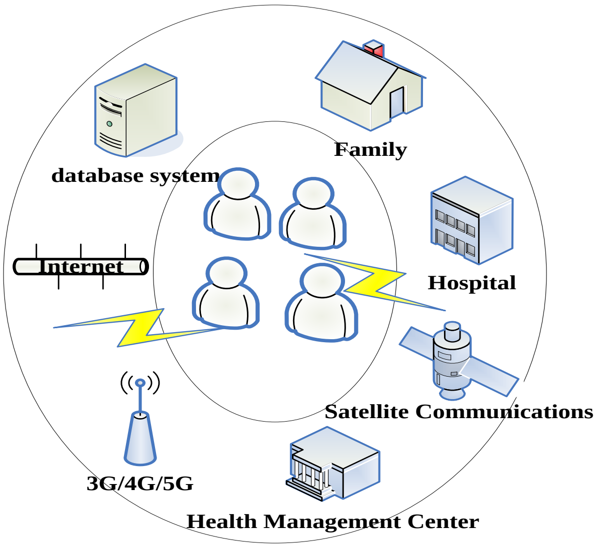

Figure 1. Health network system based on human body communication.

With the development of communication technology, wireless communication technology is gradually applied to health monitoring systems. It is generally believed that wireless communication technology mainly includes short-range wireless communication technology and medium- and long-range wireless communication technology. Among them, short-distance wireless communication technology is mainly used indoors, and long-distance wireless communication technology is mainly used outdoors [10]. Compared with traditional wired communication, wireless communication has the advantages of real-time, mobility, flexibility, and low cost. In addition, the wireless communication range is not different due to changes in the environment, the outdoor communication distance can reach tens of kilometers, and the indoor communication can also transmit hundreds of meters [11].

ZigBee technology is a medium and short-range wireless communication technology with unified technical specifications, with low output power, low transmission rate, and low power consumption as the main goals. Its physical layer and MAC layer protocol comply with IEEE802 15.4 protocol specifications. This is a new technology between traditional wireless marking technology and Bluetooth technology, and its application prospects are very broad. At present, it is mainly concentrated in the fields of industrial control, electronics, vehicle intelligence, home and building intelligence, wireless sensor networks, and medical monitoring [12].

Among them, the family health monitoring system is mainly composed of two parts: a wireless sensor network and a control terminal. The system block diagram is shown in **Figure 2**. The system continuously collects human physiological information, such as body temperature, pulse, blood pressure, etc., through various sensors installed on terminal nodes, collects and transmits to the microprocessor through the coordinator in the ZigBee wireless sensor network, analyzes and processes the collected information, and displays the result on the LCD in real time. When there is a hidden danger in the physical condition of the monitored person, the buzzer is activated to give an alarm to the monitored person, and the alarm information is sent to the preset mobile phone through the back-end GPRS module so that the family members can know the health status of the monitored person in time [13].

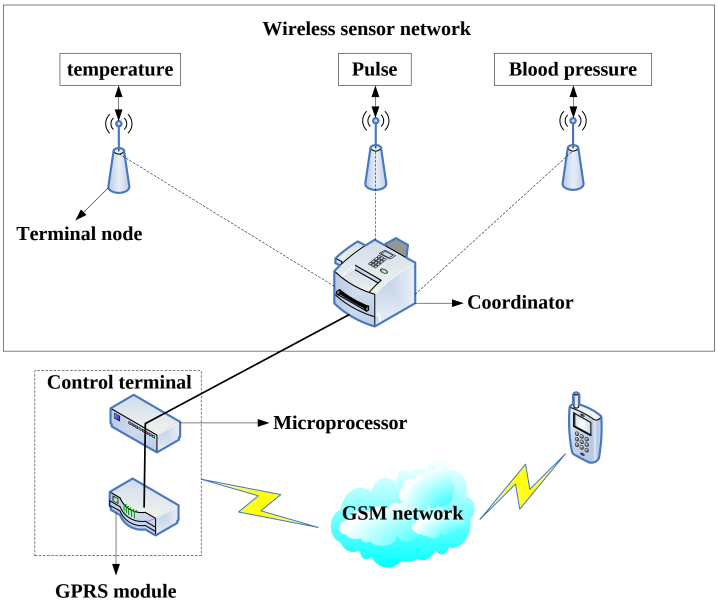

Figure 2. Overall block diagram of the system framework.

The ZigBee health monitoring system demonstrates outstanding advantages in data collection and transmission. Its low-power design ensures long-term and continuous data collection, while its real-time nature allows the system to instantly capture changes in athletes' physiological and biochemical indicators during sprint training, providing instant feedback to the coaching team. At the same time, the self-organizing network capability of the ZigBee system ensures stable data transmission and can maintain efficient operation even in complex environments.

In addition, the flexibility of the ZigBee health monitoring system is also a highlight. The system can be customized and expanded according to actual needs to meet the needs of different athletes and training scenarios. This highly customizable solution provides more accurate and personalized services for the biochemical indicator monitoring of sprinters, further improving training results and athlete performance.

3.2. Human motion recognition algorithm

When the human body makes an action, it usually lasts for a relatively long period. Therefore, the acceleration change can be selected as the state variable, and the AR (1) model (first-order autoregressive model) can be established to determine the conversion relationship between human state variables at adjacent moments [14].

The autoregressive model AR (n) is a random periodic sequence model that is very efficient in defining the field of periodic sequence [15]. In this model, the current value A_s of the time series is represented by the linear combination of the past values of the series plus a white noise disturbance term φ_{s-1}, as shown in the following formula.

$$A(s) = \mu_1 A(s-1) + \mu_2 A(s-2) + \cdots + \mu_n A(s-n) + \varphi(s-1) \tag{1}$$

This needs to know the relationship between $A(s)$ and $A(s-1)$ to build a state-space model of human body acceleration. With the method of dynamic dynamic modeling, an AR (1) model (first-order autoregressive model) is established to determine the relationship between $A(s)$ and $A(s-1)$. The model is as follows:

$$A(s) = \mu(s-1, s)A(s-1) + \varphi(s-1) \tag{2}$$

In the above formula, $\mu(s-1, s)$ represents the state conversion coefficient at time $s-1$ to time s; $\varphi(s-1)$ represents discrete white noise with a mean value of 0 and a variance of R. $\mu(s-1, s)$ and the variance R are calculated using the method of least squares estimation, as shown in the following formula:

$$L = \sum_{i=1}^{E} \varphi^2(s-1) = \sum_{i=1}^{E} [A(s) - \mu(s-1, s)A(s-1)]^2 \tag{3}$$

In the above formula, E is the number of samples obtained. The partial derivative of L concerning μ is found, and the partial derivative is set to zero, thus getting:

$$\left.\frac{\partial E}{\partial \mu}\right|_{\mu=\hat{\mu}} = 0 \tag{4}$$

$$-2\sum_{i=1}^{E} [A(s) - \hat{\mu}A(s-1)]A(s) = 0 \tag{5}$$

$$\sum_{i=1}^{E} \hat{\mu}[A(s-1)]^2 = \sum_{i=1}^{E} A(s)A(s-1) \tag{6}$$

The above formula is expressed as a vector-matrix form, and the least square estimate of $\mu(s-1, s)$ can be obtained:

$$\hat{\mu}(s-1, s) = (H^S H)^{-1} H^S C \tag{7}$$

In the above formula, there are $H = [0, A(1), A(2), \cdots A(s-1)]$ and $C = [A(1), A(2), \cdots A(1)]$;

$$\hat{R}(s-1, s) = \frac{1}{E-1}[C - H\hat{\mu}(s-1, s)]^S[C - H\hat{\mu}(s-1, s)] \tag{8}$$

When the human body is in a stable state, that is, a certain action lasts for some time, during this period CSVM approaches and remains constant. Therefore, to more accurately fit the changing trend of the human body state, Kalman filtering is performed on the state variable $A(s)$. The Kalman filter can estimate the state of the dynamic system from a series of incomplete and noisy measurements [16]. The model is shown in **Figure 3**, where circles represent vectors; squares represent matrices; asterisks represent Gaussian noise.

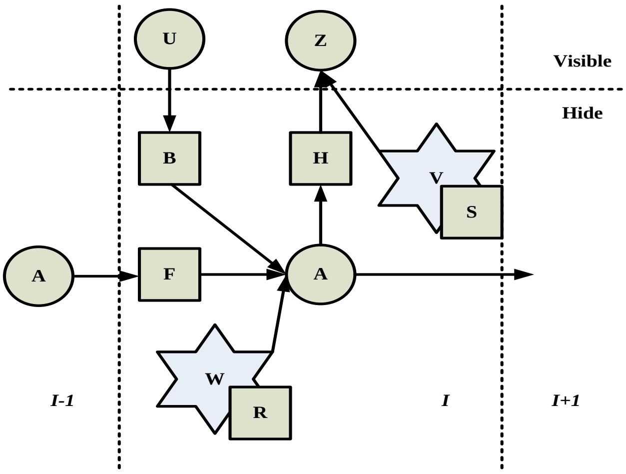

Figure 3. Kalman filter model.

The R (1) model, usually referred to as the first-order autoregressive model (AR (1)), is a simple time series prediction method. In the context of biochemical index monitoring in sprint training, the R (1) model can be used to predict the trend of changes in athletes' physiological and biochemical indicators. By analyzing historical data, the R (1) model can capture the dependencies between indicators and predict future indicator values based on this [17,18]. This prediction capability is very valuable for coaching teams because it can help them understand the possible physiological reactions of athletes in advance and formulate more scientific and reasonable training plans [19,20].

Kalman filtering is a recursive algorithm used to estimate the state of a dynamic system from a series of noisy observations [21]. In the ZigBee health monitoring system, Kalman filtering can be applied to smooth and predict the physiological and biochemical index data of athletes. By considering the dynamic characteristics of the system and the observation noise, Kalman filtering can generate a more accurate and smooth data series and reduce the impact of noise on data analysis [22,23]. This is of great significance for accurately evaluating the training status of athletes, timely discovering potential problems, and optimizing training strategies. Therefore, although the original article does not explicitly mention it, the R (1) model and Kalman filter can undoubtedly enhance the data analysis and processing capabilities of the ZigBee health monitoring system in similar application scenarios [24].

4. Experimental results of research on biochemical indicators of sprinters during training based on health monitoring

4.1. Load arrangements for sprinters in different training stages

Sprinting refers to an extremely intense cyclic running event performed by humans under the requirement of a large amount of hypoxia in the track and field engineering project. It is characterized by the shortest distance, the highest speed, the greatest strength, and the shortest running time, creating the maximum speed is also its obvious feature. Therefore, the fastest speed is the decisive factor that affects the performance of the racing competition. The statistical analysis of the sports load of racing players has always been a difficult point. Therefore, this article analyzes the number of exercises, the purpose of exercises and the content of exercises of nearly ten racing contestants in each practice stage, to clearly show the changing trend of the athletes' exercise load in each practice stage.

First of all, in the first stage of practice, most of the ten sprinters do aerobic exercise, and the amount of exercise is also large, which is mainly reflected in the average total amount of exercise per week. The training intensity at this stage is not very high, but there are aerobic exercises such as long-distance jogging. Second, in the second phase of training, although the total intensity of the athlete's training time increases significantly, the average weekly training volume is significantly smaller than that of the first phase. The total exercise intensity at this stage also increases significantly, but the proportion of speed exercises increases significantly.

4.2. Changes in blood levels of certain biochemical indicators of athletes in different training stages

In the first stage of training, the Hb values of male and female athletes show a clear downward trend. The basic value of male athletes before training is 160.2 g/100 mL. After two weeks of heavy training, it drops to 156.9 g/100 mL, and after two weeks of training, it drops to 153.3 g/100 mL. Although there is no statistically significant difference, the average drop is 4.3% before and after training. The basic value of female athletes before training is 143.6 g/100 mL, and after two weeks of large-volume training, the significant decrease is 134.8 g/100 mL ($P < 0.05$). After another two weeks of training, the change is not obvious, and its value is 134.4 g/100 mL, which is still significantly lower than before training ($P < 0.05$). **Figure 4** shows the changes in Hb (g/100 mL) of sprinters at different training stages.

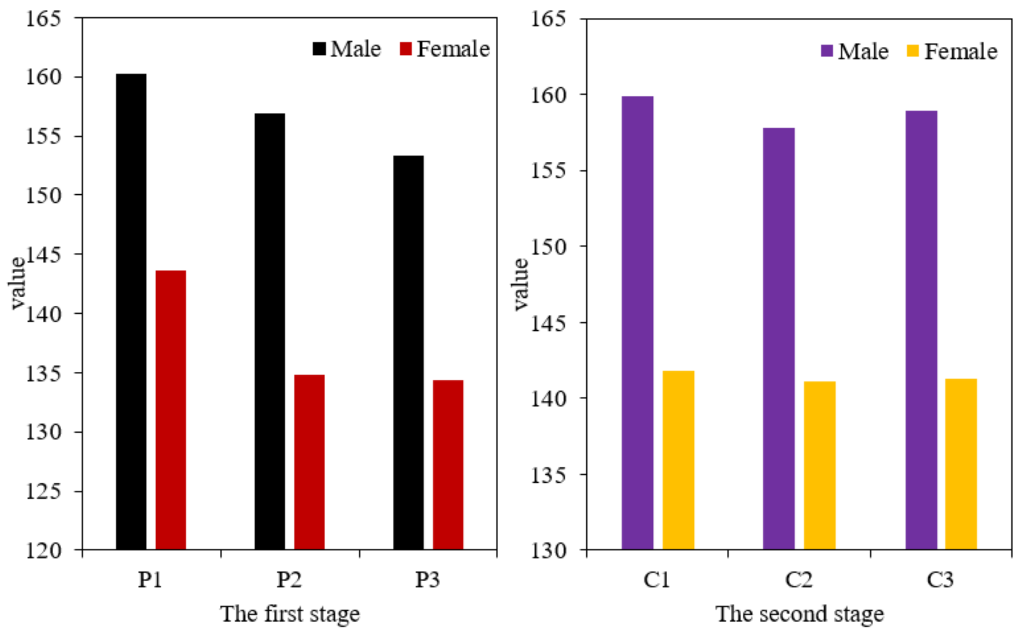

Figure 4. (a) Changes in Hb (g/100 mL) of sprinters at first stage; **(b)** Changes in Hb (g/100 mL) of sprinters at second stage.

Before and after the second stage of training, there is no significant change in the Hb values of male and female athletes. However, there is a significant difference between the Hb value of female athletes after the first stage of training and the Hb value after the second stage of training ($P < 0.05$), and the average Hb value of male athletes C3 is also higher than that of P1. It shows that training with different characteristics has a significant impact on the changes in athletes' Hb value.

The BUN (nmol/L) and creatine kinase (CK) (IU/I) fluctuations of sprinters as they progress through training are depicted in **Figures 5** and **6**, respectively. Male and female athletes' BUN values do not differ substantially throughout the two training phases, and it is uncommon for an athlete's BUN value to surpass 8 nmol/L during the data collection process. It demonstrates that the BUN value does not accurately reflect variations in sprinters' performance. In the first stage of training, sprinters' CK values do not vary much, but in the second stage, they clearly show a rising tendency. Among them, females' increase by 44.6% and males' by 65.6%, although the differences are not statistically significant ($P > 0.05$), indicating that CK can sensitively reflect changes in training intensity. However, it should be noted that the standard deviation is very large, reflecting the large differences between individuals. Therefore, in actual training, more attention should be paid to the longitudinal comparison of individual CK values.

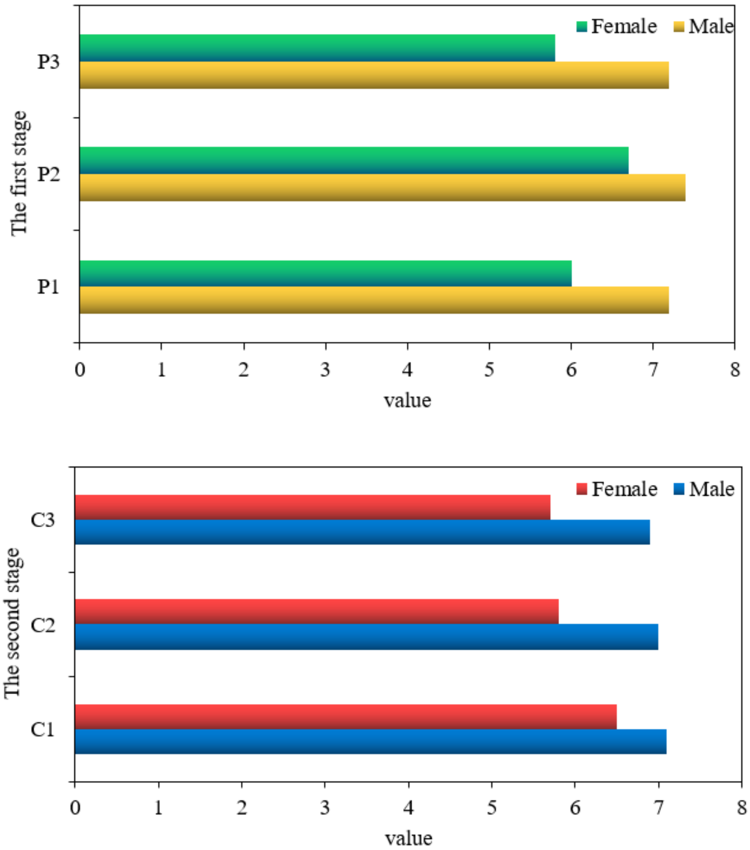

Figure 5. (a) Changes in BUN (nmol/L) of sprinters at first stage; **(b)** Changes in BUN (nmol/L) of sprinters at second stage.

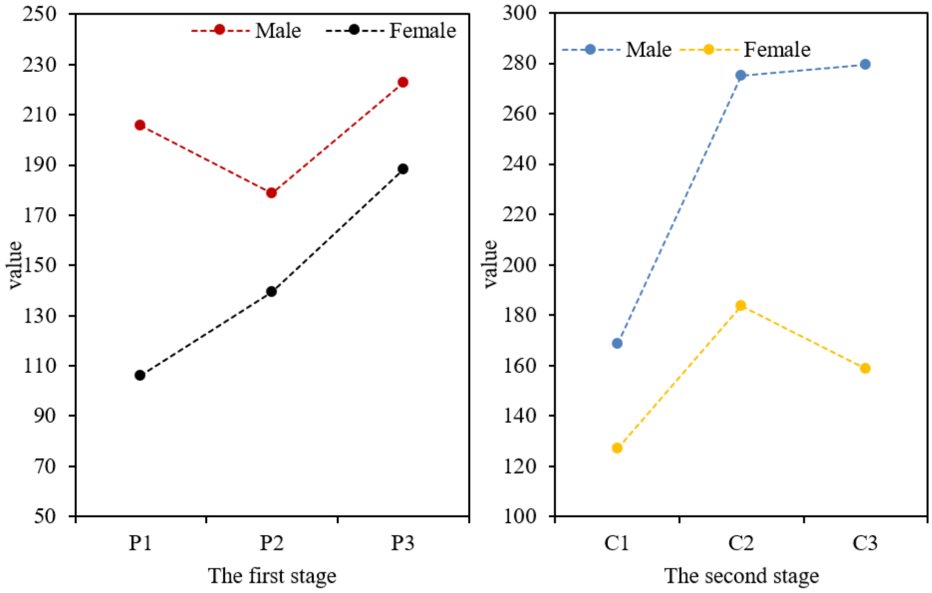

Figure 6. (a) Changes in CK (IU/I) of sprinters at first stage; **(b)** Changes in CK (IU/I) of sprinters at second stage.

The variations in T(ng/dl) during the various sprinter training periods are displayed in **Figure 7**. Male athletes' blood testosterone levels significantly decrease throughout the first stage of the exercise, averaging around a 12.8% decline from 516.2 ng/dl before the activity to 448.4 ng/dl after exercise. Male athletes' blood testosterone levels vary dramatically depending on their training stage, as seen by the large difference between the first-stage p3 and second-stage c3 blood testosterone values ($P < 0.01$).

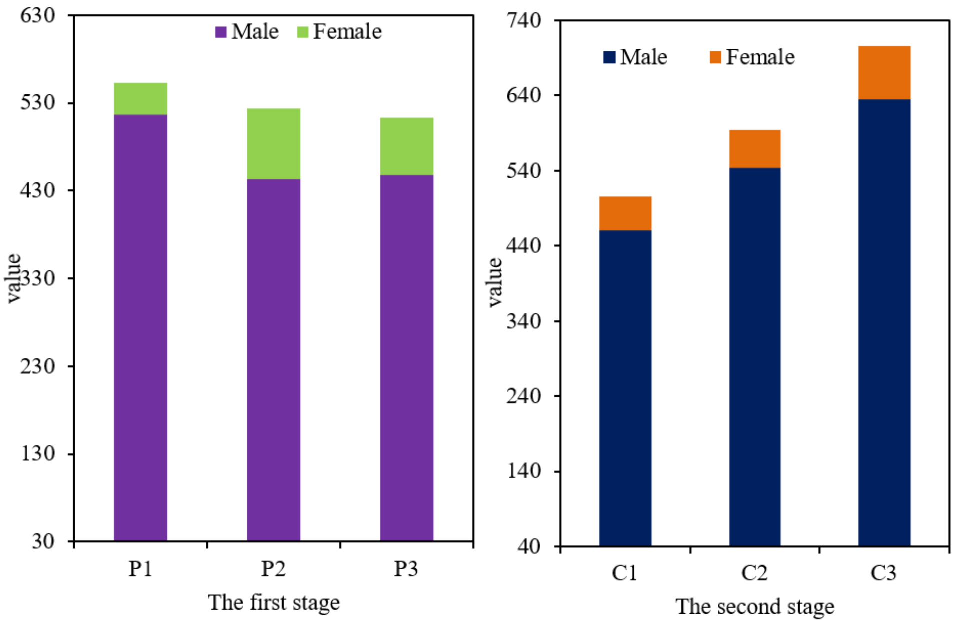

Figure 7. (a) Changes in T(ng/dl) of sprinters at first stage; **(b)** Changes in T(ng/dl) of sprinters at second stage.

The variations of C (ug/dl) in the various sprinter practice stages are displayed in **Figure 8**. Both male and female athletes' cortisol levels exhibit an increasing trend two weeks following the initial workout session. Both male and female athletes' cortisol levels decrease after two weeks of training, but they are still higher than they are before the training, suggesting that the athletes are happy with the training schedule.

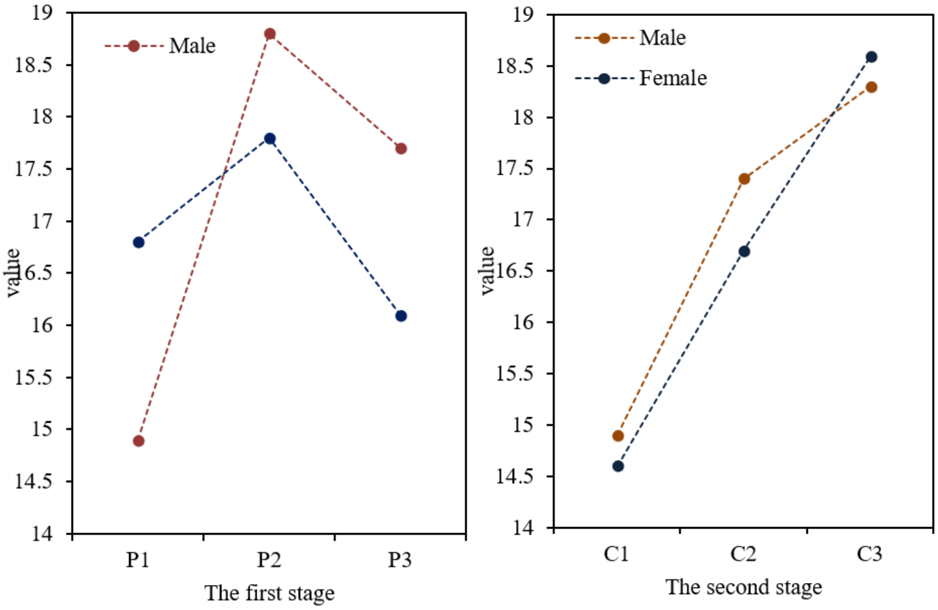

Figure 8. (a) Changes in C (ug/dl) of sprinters in first stage; **(b)** Changes in C (ug/dl) of sprinters in second stage.

In the first stage of training for male athletes, the changes in T/C show a significant decrease: from 45.1 before training to 30.2 after training. Although there is no statistical difference, the reduction is about 33%, showing that the level of decomposition and metabolism of male athletes caused by exercise increases significantly. In the second stage of training, the changes in male athletes' T/C show an upward trend. Considering that the testosterone level of the athletes in the first phase of training p3 decreases and the cortisol level increases, while in the second phase of training, testosterone increases and cortisol increases, indicating that training in each phase can make athletes reach different psychological stress states. As shown in **Table 1**, there is T/C = blood testosterone value (ng/dl)/blood cortisol value*1.26.

Table 1. T/C changes of male sprinters in different training stages.

First stage	P1	P2	P3
	45.1	30.2	32.9
Second stage	C1	C2	C3
	40.1	41.2	43.7

Table 2 is the change table of the T/C value of female sprinters in each practice stage. Female athletes experience a significant increase in testosterone levels during the first phase of training. In the second phase of training, the T/C changes similar to those of male athletes show an upward trend.

Table 2. T/C changes of female sprint athletes in different training stages.

First stage	P1	P2	P3
	2.7	5.81	5.02
Second stage	C1	C2	C3
	4.03	4.01	4.79

Table 3 shows the regular activity table of changes in serum IGF-i (ng/mL) of male sprinters during each exercise phase. The IGF-i value of male players in the first and second stages of exercise shows an upward trend. There is no significant difference between the two-stage training IGF-i within and between groups ($P > 0.05$).

Table 3. Changes of serum IGF-i (ng/mL) in male sprint athletes at different training stages.

First stage	P1	P2	P3
	419	472	529
Second stage	C1	C2	C3
	511	536	547

Table 4 shows the changes in serum IGF-i (ng/mL) of female sprinters during each exercise phase. The changes in serum IGF-i of female runners are the same as those of males. The IGF-i value of p3 after the first stage is lower than that at the beginning of the exercise. The research results show that after male and female athletes exercise, serum IGF-i levels show a significant increase, but the magnitude of this increase is not obvious.

Table 4. Changes of serum IGF-i (ng/mL) in female sprint athletes at different training stages.

First stage	P1	P2	P3
	649	637	628
Second stage	C1	C2	C3
	578	601	647

5. Discussion

The level of Hb reflects the ability of the human body to transport oxygen. People usually think that a one-time exercise causes a temporary increase in Hb levels, which is generally the result of a decrease in blood volume and an increase in viscosity [25]. However, long-term high-volume training also causes the Hb value to decrease. This is generally due to the death of a large number of red blood cells, and the new red blood cells cannot be effectively repaired [26]. The results of this study show that in the first phase of exercise, which is based on endurance exercise, the Hb values of male and female athletes show a significant decrease [27]. Before and after the second phase of training with strength training as the mainstay, the Hb value of male and female athletes does not change significantly, but the Hb value after the first phase of training is higher than that after the second phase of training. It shows that training with different characteristics has a significant impact on the changes in athletes' Hb value, and in actual training, the size of the training volume plays a decisive role in the body's Hb level.

Regarding changes in hemoglobin (Hb), its decrease may be related to high-volume aerobic exercise in the early stages of training. Heavy exercise training increases the destruction of red blood cells. At the same time, the rate of red blood cell production in the bone marrow may not keep up in time, resulting in a decrease in Hb levels. This is reflected in both male and female athletes, but the decline in female athletes is more significant, which may be related to female physiological characteristics. As training progresses and athletes gradually adapt to the training intensity, Hb levels may gradually rise or stabilize [28,29].

CK is also a key protein for the energy and metabolism of skeletal muscle cells. Under normal circumstances, the integrity and function of the bacterial cell wall are normal to ensure that CK rarely penetrates the bacterial cell wall [30]. Quantitative load exercise can also cause an increase in the activity of fresh serum enzymes. Studies usually point out that when the amount of exercise exceeds a prescribed level, it can lead to an increase in the activity of CK and lactate dehydrogenase (LDH) in the serum during and after exercise. This is generally considered to be due to the rupture of the muscle fiber that ruptures the muscle fiber layer, which in turn causes CK to appear in the blood, and CK can also reverse the degree of muscle damage [31]. This study finds that the CK value of sprinters does not change significantly in the first stage, and there is a significant upward trend in the second stage of training including a lot of strength training, indicating that the increase in strength training causes the increase in muscle fiber damage. However, the standard deviation is very large, reflecting the large differences between individuals, which should be paid attention to in actual training. The BU value reflects the normal metabolic level of the body's protein. It is generally believed that if the serum BU value is higher than 8.2 nmol/L, which is in the normal range. However, scientific research confirms that long-term low blood testosterone or high cortisol causes the body to fall into a long-term chronic proteolysis state, leading to excessive fatigue. The results of this study show that the BU values of male and female players do not change significantly during the two stages of practice, and they are all within the normal range, indicating that the BU value is not very sensitive to changes in the performance of sprinters.

A significant Increase in ckCK reflects the process of muscle damage and repair. During the stage of increased training intensity, muscle fibers may undergo micro-damage due to high-intensity exercise, causing CK to be released from the cells into the blood. Therefore, an increase in CK levels can serve as a sensitive indicator of muscle response to training load. At the same time, the increase in CK levels also promotes the repair and growth process of muscles, providing a physiological basis for athletes to adapt to higher-intensity training. It is worth noting that CK levels vary greatly between individuals, which may be related to genetics, training habits, and other factors.

6. Conclusions

In the training phase of speed training, the Hb value of racing athletes does not change significantly, and the Hb value is higher than the Hb value after the endurance training phase, but the CK value has a significant increase trend. The BU values of male and female players do not change significantly during the endurance exercise and strength exercises, and they are all within the normal range, indicating that the BU value does not respond very sensitively to the changes in the performance of mobile phones selected for racing. At the same time, the values of plasma testosterone, T/C, and serum IGF-i all show a significant increase. However, the increase in serum IGF-i is not sharply contrasted with the blood testosterone value, which shows that the effect of IGF-i on the sports stress response is not as great as the testosterone value. The significant increase in fresh serum cortisol levels is likely to be caused by the absence of pure energy training during the sprint special exercise. This study also has some shortcomings. Due to the limited sample size, only the training of nearly ten sprinters is observed, which may affect the universality and reliability of the results. In addition, the specific mechanism of changes in some biochemical indicators needs further exploration. Future research can expand the sample size and further explore the specific relationship between changes in biochemical indicators and training effects. At the same time, the ZigBee-based health monitoring system and human motion recognition algorithm need to be further optimized to more accurately guide the scientific training of sprinters.

Author contributions: Conceptualization, WH and PW; methodology, WH and PW; software, WH and PW; validation, WH and PW; formal analysis, PW; investigation, WH; resources, WH; data curation, WH; writing—original draft preparation, WH and PW; writing—review and editing, WH and PW; visualization, WH; supervision, PW; project administration, PW. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by 2023 Shandong Province Education and Teaching Research Youth Project, project number: (2023JXQ027).

Ethical approval: Not applicable.

Conflict of interest: The authors declare no conflict of interest.

References

1. Yt A, Yang L B, Ry A, et al. Change of bio-electric interferential currents of acute fatigue and recovery in male sprinters. Sports Medicine and Health Science, 2020, 2(1):25-32.
2. Miyake Y, Suga T, Otsuka M, et al. The knee extensor moment arm is associated with performance in male sprinters. European Journal of Applied Physiology, 2017, 117(3):1-7.
3. Reeta K, Timo T, Ari H, et al. Declining Physical Performance Associates with Serum FasL, miR-21, and miR-146a in Aging Sprinters. BioMed Research International, 2017, 2017(14):1-14.
4. Chtourou H, Hmida C, Souissi N. Effect of music on short-term maximal performance: sprinters vs. long distance runners. Sport Sciences for Health, 2017, 13(1):1-4.
5. Kopiczko A, M Opuszańska-Dawid, Gryko K. Bone mineral density in young adults: the influence of vitamin D status, biochemical indicators, physical activity and body composition. Archives of Osteoporosis, 2020, 15(1):1-9.
6. Verma P, Sood S K. Fog Assisted-IoT Enabled Patient Health Monitoring in Smart Homes. IEEE Internet of Things Journal, 2018, 5(3):1789-1796.
7. Padmavathy T V, Bhargava D S, Venkatesh P, et al. Design and development of microstrip patch antenna with circular and

rectangular slot for structural health monitoring. Personal and Ubiquitous Computing, 2018, 22(5-6):1-11.
8. Adam, B, Noel, et al. Structural Health Monitoring Using Wireless Sensor Networks: A Comprehensive Survey. IEEE Communications Surveys & Tutorials, 2017, 19(3):1403-1423.
9. Mizoue N. CROCO: Semi-automatic Image Analysis System for Crown Condition Assessment in Forest Health Monitoring. Journal of Forest Planning, 2017, 8(3):17-24.
10. Gui G, Pan H, Lin Z, et al. Data-driven support vector machine with optimization techniques for structural health monitoring and damage detection. KSCE Journal of Civil Engineering, 2017, 21(2):523-534.
11. Huynh T C, Dang N L, Kim J T. Advances and challenges in impedance-based structural health monitoring. Structural Monitoring and Maintenance, 2017, 4(4):301-329.
12. C, Arcadius, Tokognon, et al. Structural Health Monitoring Framework Based on Internet of Things: A Survey. IEEE Internet of Things Journal, 2017, 4(3):619-635.
13. Arnold P, Moll J, Krozer V. Design of a Sparse Antenna Array for Radar-based Structural Health Monitoring of Wind Turbine Blades. Iet Radar Sonar & Navigation, 2017, 11(8):1259-1265.
14. Janssens O, Walle R, Loccufier M, et al. Deep Learning for Infrared Thermal Image Based Machine Health Monitoring. IEEE/ASME Transactions on Mechatronics, 2018, 23(1):151-159.
15. Yasuda T, K Kawamoto, Loenneke J P, et al. Magnetic Resonance Imaging-Measured Adductor Muscle Volume and 100 m Sprint Running Performance in Female Sprinters. International Journal of Clinical Medicine, 2019, 10(10):469-476.
16. Webb B D, Gulsby S. The Forefront of SOF UAS Training. Army Aviation, 2018, 67(6):16-17.
17. Van, den, Tillaar, et al. COMPARISON OF KINEMATICS ON 30 M SPRINTS WITH 0, 10, 20, 30 AND 40% BODY WEIGHT OF ACTIVE RESISTANCE IN EXPERIENCED SPRINTERS. ISBS Proceedings Archive, 2019, 37(1):116-116.
18. Ono S, Itaya A, Hayami T, et al. Evaluation of pulse height control for rapid isometric contractions in college sprinters. Neuroreport, 2017, 28(12):766-769.
19. Kenneally-Dabrowski, Claire, Brown, et al. LATE SWING KNEE MECHANICS IN ELITE RUGBY UNION PLAYERS AND TRAINED SPRINTERS. ISBS Proceedings Archive, 2018, 36(1):207-207.
20. Wagers S M, Wareham J. Does Training and Coursework in Domestic Violence Affect Students' Perceptions of Behaviors as Domestic Violence?. Violence and Victims, 2019, 34(1):85-103.
21. Shen Y, Shi Y, Zhang J, et al. LORM: Learning to Optimize for Resource Management in Wireless Networks With Few Training Samples. IEEE Transactions on Wireless Communications, 2020, 19(1):665-679.
22. Hauta-Alus H H, Korkalo L, Freese R, et al. Urban and rural dietary patterns are associated with anthropometric and biochemical indicators of nutritional status of adolescent Mozambican girls.. Public Health Nutrition, 2018, 21(6):1-8.
23. Zhou W, Liu Y, Zheng W. Seismic performance of self-centering concrete shear wall: State-of-the-art review and prospects. Harbin Gongye Daxue Xuebao/Journal of Harbin Institute of Technology, 2018, 50(12):1-13.
24. Kongar I, Giovinazzi S, Rossetto T. Seismic performance of buried electrical cables: evidence-based repair rates and fragility functions. Bulletin of Earthquake Engineering, 2017, 15(7):3151-3181.
25. Płoszczyca K, Czuba M, Chalimoniuk M, Gajda R, Baranowski M. Red Blood Cell 2,3-Diphosphoglycerate Decreases in Response to a 30 km Time Trial Under Hypoxia in Cyclists. Front Physiol. 2021;12:670977. Published 2021 Jun 15. Doi:10.3389/fphys.2021.670977
26. Alberty R, PupiŠ M, VachalÍk V, BátovskÝ M. Diurnal variation in red blood cell variables in athletes after single and repeated bouts of exercise. J Sports Med Phys Fitness. 2021;61(2):269-279. Doi:10.23736/S0022-4707.20.11174-5
27. Sitkowski, D., Klusiewicz, A., Pokrywka, A., et al. (2023). Relationships between Changes in Hematological Adaptations and Exercise Capacity in Olympic Rowers after a Period of Reduced Training Loads. Journal of human kinetics, 86, 155–164. https://doi.org/10.5114/jhk/159463
28. Mujika I, Bourdillon N, Zelenkova I, et al. (2024) Hematological and performance adaptations to altitude training (2,320 m) in elite middle-distance and distance swimmers. Front. Physiol. 15:1474479. doi: 10.3389/fphys.2024.1474479
29. Périard JD, Girard O, Townsend N, et al. Hematological Adaptations Following a Training Camp in Hot and/or Hypoxic Conditions in Elite Rugby Union Players. Int J Sports Physiol Perform. 2023;18(9):1053-1061. Published 2023 Aug 16. doi:10.1123/ijspp.2023-0166
30. Hargreaves, M., Spriet, L.L. Skeletal muscle energy metabolism during exercise. Nat Metab 2, 817–828 (2020). https://doi.org/10.1038/s42255-020-0251-4
31. Leite CDFC, Zovico PVC, Rica RL, et al. Exercise-Induced Muscle Damage after a High-Intensity Interval Exercise

Session: Systematic Review. International Journal of Environmental Research and Public Health. 2023; 20(22):7082. https://doi.org/10.3390/ijerph20227082