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Current and Potential Applications of Wearables in Sports Cardiology

Prashant Rao¹, Dhruv R. Seshadri², Jeffrey J. Hsu^{3,4}

¹Cardiovascular Division, Beth Israel Deaconess Medical Center, Harvard Medical School, Boston, MA, United States.

²Department of Biomedical Engineering, Case Western Reserve University, Cleveland, OH, United States,

³Division of Cardiology, David Geffen School of Medicine at UCLA, Los Angeles, CA, United States.

⁴Division of Cardiology, Veteran Affairs Greater Los Angeles Healthcare System, Los Angeles, CA.

Abstract

Purpose of the review: Commercial wearable biosensors are commonly used among athletes and highly active individuals, although their value in sports cardiology is not well established. In this review, we discuss the evidence for the current applications of wearables and provide our outlook for promising future directions of this emerging field.

Recent findings: The integration of routine assessment of physiological parameters, activity data, and features such as electrocardiogram recording has generated excitement over a role for wearables to help diagnose and monitor cardiovascular disease. Presently, however, there are significant challenges limiting their routine clinical use. While studies suggest that wearable-derived data may help guide training, evidence for the use of wearables in guiding exercise regimens for individuals with cardiovascular disease is lacking. Further, there is a paucity of data to demonstrate its efficacy in detecting exercise-related arrhythmias or conditions associated with sudden cardiac death. Further technological developments may lead to a greater potential for wearables to aid in sports cardiology practice.

Summary: The ability to collect vast amounts of physiological information can help athletes personalize training regimens. However, interpretation of these data and separating the signal from the noise are paramount, especially when used in a clinical setting. While there are currently no standardized approaches for the use of wearable-derived data in sports cardiology, we outline three domains in which they could guide the care of athletes in the future: (1) optimizing athletic performance (2) guiding exercise in athletes with known cardiovascular disease, and (3) screening for cardiovascular disease.

Corresponding Author: Jeffrey J. Hsu, M.D., Ph.D., 650 Charles E. Young Drive South, CHS A2-237, Los Angeles, CA 90095-1679, jjhsu@mednet.ucla.edu.

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Keywords

Wearables; sports cardiology; athlete; cardiovascular performance; recovery

Introduction

Advances in digital technologies have led to the rapid uptake of commercial wearable biosensors (hereafter called “wearables”) among consumers in the general public, including athletes. At present, 20% of United States residents currently own a smart wearable device, with the market expected to exceed 929 million connected devices this year.¹ Wearables are relatively low-cost technology that have a wide variety of potential uses, including monitoring for arrhythmia and hemodynamic changes, tracking physical activity and calorie expenditure, as well as providing information about general health and well-being. Furthermore, these devices can be accessed through smartphone technologies to provide almost instantaneous feedback about personal health metrics in real time to the user.

Many athletes and highly active individuals already use wearables (e.g., Polar chest straps (Polar Electro, Finland), Garmin (Garmin, USA) and Apple (Apple Inc, Cupertino, CA) watches) to monitor personal health metrics and quantify fitness levels and performance. With their rise in popularity, wearables have garnered the attention of sports cardiologists for their potential clinical utility. From detecting exercise-related arrhythmias and identifying subclinical cardiac pathology to providing information about training and recovery, the possible roles for wearables in cardiology practice appear broad at first glance, with the goal of reducing the risk of exercise-related adverse cardiac events and improving cardiovascular performance. However, these hopes have been tempered by a number of factors, particularly data accuracy and lack of actionable information. As sensor technologies mature and their use among the general and athlete population increases,² it will be important for physicians to not only recognize their utility and benefits, but even more critically adjudicate such technologies to evaluate their potential and limitations. For instance, false positive alerts for suspected arrhythmias may cause unwarranted anxiety in asymptomatic individuals, generate unnecessary and costly tests, and, at worst, lead to inappropriate disqualification from sports participation. Furthermore, at present, there is no clear benefit of biosensors in relation to health care costs or utilization,³ and professional societies have raised concerns about the routine use of wearables for electrophysiologic monitoring in the community.⁴

In this review, we provide an overview of commercially available and commonly used wearables and discuss the evidence for their utility (or current lack thereof) among regular exercisers and athletes. Additionally, we discuss our outlook for promising future directions of this emerging field.

Types and Capabilities of Wearables

Popular wearables include chest straps, watches, wristbands, and rings⁵⁻⁷ (Figure 1). In the past decade, wearables have progressed from being primarily step-counters and fitness-trackers, to recording both physiological and activity-related data with enhanced connectivity.

Physiological Sensors

Physiological measurements that are monitored by currently available wearables include but are not limited to heart rate (HR), heart rate variability (HRV), respiratory rate (RR), blood oxygen saturation (SpO₂), and skin temperature. More recent devices have the ability to estimate VO₂max, a measure of aerobic capacity.

Measurement of Heart Rate During Exercise

In order to measure HR and SpO₂, most wearables use photoplethysmography (PPG) technology, which is an optical volumetric assessment of blood volume changes in the microvasculature.⁸ This technology assesses small volume changes by illuminating the capillary bed with a small light source (such as an LED, e.g. 365 nm wavelength). The intensity of light transmitted through or reflected from the bed is then measured by a photodiode.⁹ Over a wide range of HR at rest, there are no detectable differences between a traditional vital signs monitor used in clinical settings and many commercial wearables.¹⁰ Furthermore, commercial wearables correlate fairly well with standard electrocardiographic (ECG) monitoring during aerobic exercise.¹¹ Among both healthy adult volunteers and patients enrolled in cardiac rehabilitation, chest strap monitors (Polar H7) have the best agreement with ECG ($r = 0.99$), whereas optically based wrist-worn HR monitors vary across models with generally lower accuracy ($r = 0.52-0.92$).^{11,12} Importantly, the performance of wrist-worn HR monitors varies with exercise modality, and overall, they perform poorly during elliptical trainer activity with use of arm levers (all $r < 0.80$).¹¹ In comparison of commonly used wrist-worn wearables, the Apple Watch Series III shows the best agreement with ECG monitoring on the treadmill at various speeds ($r = 0.96$), while other tested devices (Fitbit Iconic (Fitbit, USA), Garmin Vivosmart HR, Tom Tom Spark 3 (TomTom, Netherlands)) have similarly lesser agreement ($r = 0.89$).¹³ It is important to also consider that skin color, moisture, and tattoos may affect the accuracy of wrist-worn monitors.¹⁴ In summary, given the variable performance across optically based wrist-worn monitors, data from these devices should be interpreted with caution, and chest strap monitors should be considered if more accurate ambulatory HR measurements during exercise are required for clinical or performance purposes.

More recently, smartwatches have introduced direct ECG electrode recording for heart rate and rhythm monitoring. Some smartwatches, such as the Apple Watch and the Fitbit Sense, can record a lead I-like rhythm strip by incorporating a negative and positive electrode on the side and back of the watch, respectively. Therefore, in order to record a single-lead ECG using the Apple Watch, the user simply places a finger of the contralateral hand on the digital crown. In addition, certain manoeuvres can be performed to obtain leads II and III (by moving the watch to the ankle and placing the right or left hand on the digital crown for lead II and II, respectively), and the precordial leads can also be acquired through manipulation of the device.¹⁵ This capability therefore offers individuals continuous PPG heart rhythm monitoring with single-lead ECG monitoring as needed.

Activity-related Sensors

In addition to physiological metrics, wearables can also precisely capture activity-related parameters, such as walking, cycling, running, and other activities. This capability is

facilitated through the use of biaxial or triaxial accelerometers to measure movement and changes in motion based on principles of inertia. Accelerometers are often used in conjunction with global positioning systems to assess precise positioning in space during movement, barometers to detect changes in altitude/elevation, and gyroscopes to measure angular motion.¹⁶

Respiratory Rate Sensors

PPG exhibits respiratory modulations that are used by wearables to develop algorithms to estimate respiratory rate.^{17,18} These modulations include baseline wander, amplitude modulation, and frequency modulation, and are well summarized here.¹⁹ In short, changes in tissue blood volume detected by PPG occur due to i) reduced stroke volume during inspiration (due to reduced intrathoracic pressure) ii) arterial vasoconstriction during inspiration iii) increased HR in inspiration (baroreflex-mediated response to decreased stroke volume). These modulations differ across demographics; for example, frequency modulation-based respiratory signals are of lower quality in elderly individuals.²⁰ A plethora of PPG-derived RR algorithms are reported in the literature, and many wearables use these algorithms to provide estimates of RR.¹⁹

VO2max Estimation

Data collected from HR and activity-related sensors can be used to derive surrogate measurements of other physiological data such as energy expenditure²¹⁻²³ and VO2max. Several formulae have been used to predict VO2max ranging from simple to complex. For example, the formula “VO2max = 15.3 × (HRmax/HRrest)” estimates VO2max in well-trained men with a standard error of estimate of 0.21 l/min or 2.7 ml/min/kg.²⁴ By contrast, complex mathematical modeling and machine learning techniques, namely artificial neural networks (ANN), use more variables such as demographic information (age, sex, height, weight), HR, and activity-related data to estimate VO2max with similar precision.²⁵

Implementation of Wearables in Sports Cardiology

Wearables to Screen for Cardiovascular Disease in Athletes

In sports cardiology, wearables may play an important role in risk stratification and prevention of sudden cardiac death (SCD) in athletes. Intense exercise may trigger ventricular arrhythmias in any individual with an underlying cardiac defect associated with SCD. While the true incidence of SCD in athletes remains uncertain and is influenced by age, sex and sport, it is reported to be as high as 1:15,000 among male adolescent soccer players.²⁶ Although an ambitious goal, in the future, it is conceivable that wearables may hold the potential to facilitate detection of otherwise undiagnosed exercise-related arrhythmias in athletes with underlying cardiovascular disease. More ambitious still, through algorithm development and refinement, future wearables may provide automated health event prediction, identifying at-risk athletes whom would otherwise go undetected with traditional screening measures. Ultimately, these advances could lead to early recognition of conditions associated with SCD in athletes, with the intention to subsequently modify SCD risk in these individuals.

An important cause of SCD in young athletes is Long QT syndrome. Limited data suggest that using ECG equivalents of lead I, II, and V6, ECG tracings from the Apple Watch Series 4 allow for adequate QT interval measurements in 85% of patients in sinus rhythm, with the major limitation being ECG tracing quality and T-wave amplitude.²⁷ Although the feasibility of remote detection of Long QT syndrome using wearables is yet to be proven, it is plausible that these devices may provide an opportunity to screen large numbers of young individuals for this condition in the future.

While it is not currently possible, nor feasible, to use wearables to accurately screen for other conditions associated with SCD in athletes, a growing body of evidence suggest that wearables may be used to identify arrhythmias, namely atrial fibrillation. In the Apple Heart Study, which virtually enrolled 419,297 participants within 8 months, a PPG-based algorithm detected an irregular pulse in 0.52% of participants.²⁸ Of note, only 0.16% of those aged between 22 to 40 years received a notification compared to 3.1% of individuals 65 years and older. Of all study participants who had irregular pulse notifications during simultaneous use of an ECG patch, the positive predictive value for the irregular pulse notification was 84%. In the Huawei Heart Study that used smart devices to monitor the pulse rhythm, 424 out of 187,912 participants received a notification for suspected atrial fibrillation. Consistent with the findings from the Apple Heart Study, of the 62% of notified participants that pursued medical evaluation, the PPV of the Huawei Heart Study algorithm was 87%.²⁹ Given that atrial fibrillation is more prevalent in male masters endurance athletes than the general population, the PPV in theory may in fact be higher in this specific athlete population.³⁰

Wearables to Guide Exercise Training Regimens

Heart Rate Zone-Guided Training: Wearables provide an opportunity for individuals to use HR as a tool to guide training intensity. This concept may be useful in creating training regimens for athletes as well as developing personalized exercise prescriptions for patients with cardiac disease. For example, popular endurance training regimens involve long periods of aerobic exercise at an intensity whereby lactate production does not exceed clearance (commonly referred to as Zone 2) coupled with high-intensity interval training (HIIT), which involves repeated, short bouts of high intensity efforts. For many individuals, specific training intensities can be most accurately ascertained by performing a cardiopulmonary exercise test. Once these intensities are determined, the correlated heart rate at the given intensity can be used as a proxy to guide future training sessions. For athletes without access to a cardiopulmonary exercise test, both heart rate zone- and HIIT training can be estimated, with specific zones determined as a percentage of predicted maximal heart rate for an individual.

In addition, providing safe exercise recommendations for athletes with coronary artery disease or conditions associated with SCD is an important, challenging, and evolving area of sports cardiology. While the American Heart Association and the American College of Cardiology recommendations for many of these conditions include restricting athletes to low intensity (i.e., Class IA) competitive sports,³¹ recent updates recommend a more liberal approach, especially when the relationship between exercise and the progression of

disease/risk of SCD remains unclear.³² It follows that wearables, through the potential to provide real-time objective feedback to patients during exercise, may help ensure adherence to certain training intensities. Importantly, a wearable-based strategy for athletes with known cardiovascular disease demands demonstration of the accuracy of the device and of the clinical safety and utility in patients in a clinical trial. Perhaps the growing interest of home-based cardiac rehabilitation for patients with underlying cardiovascular disease may result in demonstrating the accuracy, safety, and efficacy of wearables in this population.³³

As mentioned earlier, the accuracy of wrist-worn HR monitors varies considerably, especially during exercises that involve significant arm movement. Thus, when counseling athletes on HR-guided training regimens, or providing heart rate guided exercise prescriptions for individuals with underlying cardiac conditions, it is important to understand the accuracy limitations of wearables, with the most accurate guidance likely to result from the use of a chest strap monitor.

Heart Rate Variability-guided Training: In addition to HR metrics, wearable devices present an opportunity to provide objective data related to internal workload and recovery. While external workload is defined as the output exerted by an athlete (generally quantified based on biomechanical movements quantified through acceleration and velocity), internal workload represents the physiological response to the external load. Internal workload is commonly measured using wellness questionnaires aimed at gauging the athlete's response to prior workouts as well as recent levels of stress, recovery, and/or sleep.^{34,35} Internal workload also comprises of subjective scaled assessments during exercise (e.g rating of perceived exertion (RPE) using the Borg's or Foster's Scale). RPE and the duration of the training session helps to guide sports scientists to quantify the internal workload of the athlete during a particular workout. These metrics can then be used by training and coaching staff to determine whether there is sufficient recovery between training sessions (Table 1). In competitive sports, it is well established that recovery is important to prevent injury and training plateaus. Overreaching, and possibly overtraining may develop when there is a lack of balance between training load/stress and recovery (Figure 2).³⁶

Due the subjective nature of wellness questionnaires and RPE, objective data from wearables may be used to complement these assessments in order to more accurately determine the internal workload profile of athletes. Specifically, variations in skin temperature and RR from baseline circadian patterns, as well as the measurement of HRV in particular are increasingly being used as an objective marker of internal workload and recovery by wearable devices. HRV represents changes in patterns of the autonomic nervous system and may function as a holistic assessment of training, sleep, nutrition, psychological and emotional stress. Kiviniemi et al studied whether the use of daily HRV measurements as part of an endurance training strategy could result in a better training response compared to a pre-defined training program in healthy, moderately fit male endurance athletes.³⁷ Using a Polar S810i heart rate monitor, HRV was calculated each morning using Polar software. When HRV decreased, training intensity for that day was decreased compared to the previous day. When HRV increased or remained the same, training intensity increased. A maximum of two consecutive high-intensity exercise days and resting days were allowed, and rest was prescribed after 9 consecutive days of training regardless of HRV that day.

Despite similar training frequencies (6 times per week) and fewer high-intensity workouts (3/week vs 4/week in the pre-defined training program), athletes who followed an HRV-guided training protocol had significantly greater changes in their maximal running velocity achieved on maximal exercise testing, and a greater (but not statistically significant) increase in VO₂peak. The same group performed a similar analysis on both men and women.³⁸ While the findings were consistent with previous observations in men, women in the HRV-guided group had similar improvements in cardiovascular performance with a lower training load. These findings are supported by subsequent studies showing greater improvement in athletic performance using HRV guided training regimens.^{39,40} It is important to note that there are several limitations pertaining to the accuracy of wearables to measure HRV. Some studies assessing the effectiveness of HRV guided training use a 7-day rolling average of root mean square of successive differences (RMSSD) between normal heartbeats because it is thought that this is more sensitive to detect changes in the training status compared with single-day measurements.⁴¹ Taken together, despite the limitations in obtaining accurate HRV data and the challenges in interpreting its significance, it is plausible wearable-derived HRV can help guide training regimens to provide marginal gains in performance.

Collaborate to Compete: Integrating Basic Science and Sports Cardiology

Further advances in material science, manufacturing, and data analytics will generate more data for the user and physician and at a lower cost, making wearables a ubiquitous item, much like the personal computer of the past and smartphones of today.⁴² All devices in the market today leverage silicon-based process technology. Silicon chips are now able to be made very thin (~50 um) and can be stacked in three dimensions to enable complex sensing, signal processing, data storage and communication capabilities in a small unit volume.^{43,44} Silicon technology can also be integrated in epidermal sensors. Recently, nanomaterial-based flexible sensors have garnered increased attention due to their interaction with the human body. These materials can be attached onto clothing⁴⁵ or applied directly on skin for real-time monitoring of various physical, chemical, biological, and environmental signals,⁴⁶⁻⁴⁹ thus making them extremely promising for sports-related applications.⁵⁰ Such developments can enable the measurement of biochemical markers, such as sodium, potassium, lactate, cortisol and other physiological markers related to exercise. Gatorade (in collaboration with Epicore Biosystems) recently commercialized the Gx Sweat Patch, an epifluidic calorimetric system that wicks eccrine sweat and measures whole body sweat rate, hydration status, and sodium loss. Whether the real-time assessment of these analytes provide clinically meaningful data that can contribute to the assessment and monitoring of sports cardiology patients remains to be determined.

Conclusion

Athletes are continually searching for new approaches to efficiently maximize performance while reducing injury burden. An ever-increasing ability to collect physiological information can help with this mission through personalizing training regimens and making athletes aware of the importance of recovery. For sports cardiologists and athletes alike, it will be of paramount importance to understand how best to interpret and use the plethora of information and separate the signal from the noise. As technologies mature, and exercise

recommendations for athletes with cardiac conditions become less restrictive, wearables may be an important tool to both monitor the safety of exercise in athletes with cardiac conditions as well as detect, and even predict, de novo disease. While there currently are no standardized approaches or guidelines to implementing the use of wearable-derived data in sports cardiology practice, we envision three domains in which they could guide care of athletes: (1) screening for cardiovascular disease, (2) improving cardiovascular performance, and (3) guiding exercise in athletes with known cardiovascular disease (Figure 3).

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	Apple Watch	Catapult Vector	Fitbit	Garmin	Kenzen	Oura Ring	Polar	Qardio	Whoop	VivaLNK Vital Scout	AliveCor	Zio Patch	Gatorade Gx Sweat Patch
Price	\$400	> \$1500	\$150	\$400	N/A	\$299	\$100	\$500	\$30/mo	\$150	\$150	\$360*	\$25 (pack of 2)
Analytics	X				X	X	X	X	X	X	X	X	X
HR	X		X	X	X	X	X	X	X	X	X	X	X
RR	X							X	X	X	X	X	
HRV	X							X	X	X	X	X	
Heart Rhythm	X							X		X	X	X	
Blood Oxygen Saturation	X												
External Load		X											
Internal Load				X			X						
Recovery				X			X		x				
Steps	X		X	X			X	X					
Distance	X	X	X	X			X	X	s				
Sleep	X		X	X			X	X	X				
Pedometer	X		X	X			X	X					
Calories	X		X	X			X	X		X			
Stress									X				
Strain									X				
Skin Temp					X	X		X		X			
Whole Body Sweat Rate													X
Sodium Concentration													X

Figure 1.
Commercially available wearable sensors for physiological and biochemical monitoring

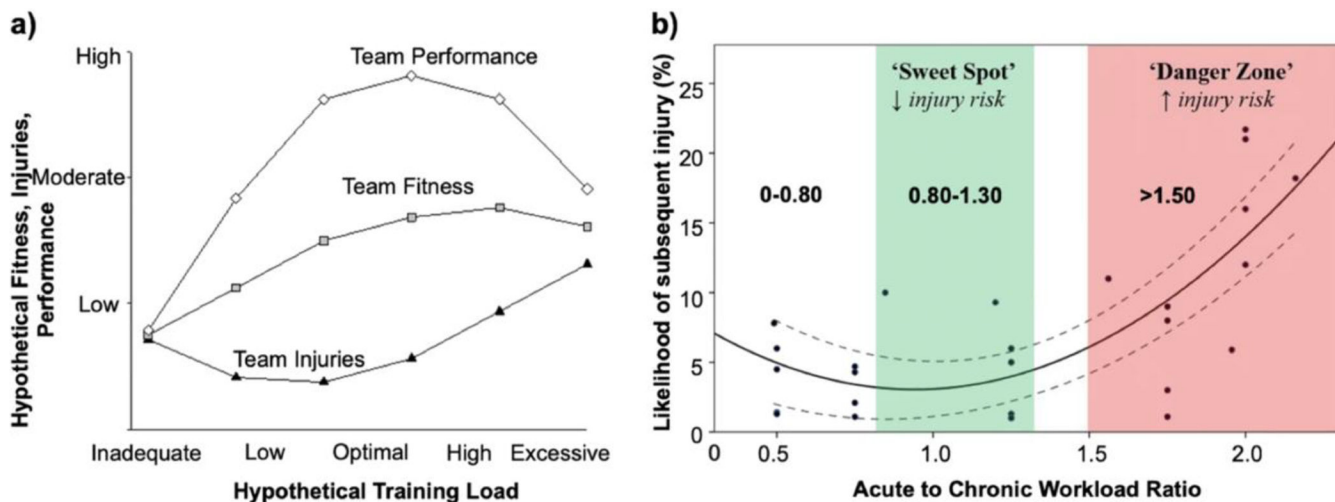


Figure 2. Relationship between workload, team fitness, and team performance. (a) Hypothetical relationship between training loads, fitness, injuries, and performance. Inadequate and excessive training loads could result in increased injuries, reduced fitness, and poor team performance. (b) Interpreting and applying training load data to assess the likelihood of subsequent injury. Modified and used with permission from Gabbett et al.³⁵

Potential Clinical Utility for Wearables in Sports Cardiology Practice




			
	Improving Athletic Performance	Screening for Cardiovascular Conditions	Guiding Exercise in Athletes with Cardiac Disease
Examples	Heart rate-guided training Heart rate variability-guided training	Atrial arrhythmia detection	Measuring appropriate levels of exercise intensity in patients with HCM, ARVC, etc.
Data	Javaloyes et al., 2019 Vesterinen et al., 2016 Daussin et al., 2008 Kiviniemi et al., 2007	Guo et al., 2019 Perez et al., 2019	None

Figure 3. Potential clinical utility for wearables in sports cardiology practice.

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Table 1.

Subjective and Objective Methods used to Quantify Internal Workload. RPE: Rating of Perceived Exertion (RPE); Training Impulse Response (TRIMP); Workload (WL); D = duration of training session in minutes; HR_{ex} is average heart rate of the exercise; session, HR_{rest} is resting heart rate; HR_{max} is maximal heart rate.

Method	Description	Equation: Internal WL =	Wearables Exists to Measure?
Subjective Measures			
Borg's RPE Scale	Scale from 6–20 with increases in workout intensity correlating with increased score	Session RPE * Duration (minutes)	No
Foster's RPE Scale	Scale from 1–10 with increases in workout intensity correlating with increased score	Session RPE * Duration (minutes)	No
Objective Measures			
Banister TRIMP	Length of the session (in minutes) multiplied by an intensity factor defined for both men and women	$D * (A * HR * \exp^{(B * HR)})$ A = 0.64 (men); 0.86 (women) B = 1.92 (men); 1.67 (women) $HR = (HR_{ex} - HR_{rest}) / (HR_{max} - HR_{rest})$	Yes
Morton's TRIMP	Similar to Banister's TRIMP model, except gives greater weight to high-intensity training	$D * (A * HR * 2.718 \exp^{(B * HR)})$ A = 0.64 (men); 0.86 (women) B = 1.92 (men); 1.67 (women) $HR = (HR_{ex} - HR_{rest}) / (HR_{max} - HR_{rest})$	Yes
Edwards TRIMP	Summation of the HR zone score method. Product of the cumulated training duration (in minutes) for 5 heart rate zones multiplied by a coefficient relative to each zone Zone 1: 50%–60% HR_{max} Zone 2: 60%–70% HR_{max} Zone 3: 70%–80% HR_{max} Zone 4: 80%–90% HR_{max} Zone 5: 90%–100% HR_{max}	duration in zone 1 * 1 + duration in zone 2 * 2 + duration in zone 3 * 3 + duration in zone 4 * 4 + duration in zone 5 * 5	Yes
Lucia TRIMP	Individually determined lactate thresholds and the onset of blood lactate [La] accumulation. The duration spent in each of three heart rate zones (zone 1: below the ventilator threshold; zone 2: between the ventilator threshold and the respiratory compensation point and zone 3: above the respiratory compensation point) is multiplied by a coefficient (k) relative to each zone (k = 1 for zone 1, k = 2 for zone 2, and k = 3 for zone 3) and the adjusted scores are then summated	duration in zone 1 * 1 + duration in zone 2 * 2 + duration in zone 3 * 3	Yes
Stagno TRIMP	Modified version of the Banister's TRIMP to quantify training load based on the direct measurement of the athletes' [La] profile.	$D * HR * 0.1225 * \exp^{(3.9434 * HR)}$	Yes
LacTRIMP	Training load is calculated through [La] concentration. Three intensity zones were adopted (zone 1: [La] < 2, zone 2: 2 > [La] < 4, zone 3: [La] > 4). A relative coefficient was attributed to each zone (k = 1, for zone 1; k = 2, for zone 2; and k = 3, for zone 3). The LacTRIMP was calculated by the sum of the multiplications of the times spent in the different zones by the coefficient relative to each zone	duration in zone 1 * 1 + duration in zone 2 * 2 + duration in zone 3 * 3 + duration in zone 4 * 4	No