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The Application and Development Trends of Wearable Devices (WD) in Endurance Sports Training：A Literature Review

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Abstract:

Collecting and organizing information on the application of technology products such as wearable devices, intelligent training, and the Internet of Things (IoT) in endurance sports training from 2005 to 2023, it was found

that wearable devices, heart rate bands, bicycle power devices, intelligent training device applications, and sports community platforms can be connected through the Internet of Things, and data can be automatically shared, Furthermore, provide feedback on the workload and training effectiveness of sports training; The long-distance supervision and virtual coaching system of real coaches support direct interaction between athletes and real coaches, which can promote athletes' training motivation, improve sports performance, and have a good positive effect on enhancing athletes' completion of training plans; Intelligent wearable equipment can accurately provide HR and HRV parameters, based on which training load and maximum oxygen uptake can be evaluated, providing a basis for adjusting training strategies and ensuring maximum training benefits.

Keywords Wearable Devices ; internet of things ; Intelligent training device; Data management system; Virtual reality sports platform

1 Introduction

WD refers to a lightweight microcomputer device that can be worn on the human body to extract relevant information, and react and transmit data to personal action devices (Monoli et al, 2023; McFadden, 2021). In recent years, WD and IoT innovation have promoted the popularization of intelligent training and increased the market growth rate of sports technology products. Technological and personalized training equipment, virtual environments, and e-coaching systems are highly favored by amateur and professional endurance athletes. Especially some commercial WD, For example, smart watches, smart sports wristbands, mobile health devices, and health applications (apps) for smartphones have innovative devices that combine humanistic and humanized functions, as well as multiple functions such as review, real-time feedback, and warning, forming a new favorite of the current sports trend (Patel et al, 2015; Silfee et al, 2018). According to the 2016 Global Fitness Trends Forecast Report, the importance of wearable technology development as a trend has ranked first. In the 2020 Global Fitness Trends Survey Report by the American College of Sports Medicine (ACSW), wearable technology equipment was also listed as the number one intelligent auxiliary tool for sports training (Huhn et al, 2022).

The key to the effectiveness of endurance training is to prevent and reduce sports injuries, maintain the smoothness and persistence of training, and one of the main reasons for inducing sports injuries is overtraining and how to exert force correctly during exercise. Nowadays, WD has been widely applied in various sports, such as swimming, running, ball games, etc. (Mooney et al, 2015; Lee, Mellifont, & Burkett, 2010; Galli et al, 2023; Biagetti et al, 2018). In typical endurance sports, the triathlon includes swimming, cycling, and running, among which the improvement of swimming's competitive strength requires technical training and specialized physical training. In addition to helping to improve the competitive strength of swimmers, especially the training of water sensation, it mainly includes proprioception (sensation of water) and the ability to control water (Yuhui & Ruihong, 2008). Therefore, it is very important to achieve precise regulation of load in sports training. With the promotion and application of emerging intelligent technology products in the field of sports science, these smart wearable devices can provide athletes with reliable and easy to explain movement performance characteristics, internal and external load differences, prevention and identification of injuries, etc., thereby promoting the understanding of training and competition processes by relevant personnel, and assisting in planning training content and recovery tasks. WD can quantify and accumulate long-term records of relevant technical indicators during the training process, and run them on big data between devices and the cloud. After analysis, it provides academic research or technological development, and meaningful information is fed back to users (Bourdon et al, 2017; Jianxufang, Yinxin, & Ziyuan, 2016). Therefore, this article aims to use literature analysis method, with endurance sports intelligent training such as long-distance running, football, and triathlon as the main literature. Through literature analysis method, it explores the current monitoring methods of sports training load, system method data management, mixed reality sports platforms, and new trends in intelligent technology research; Identify key points, evaluate shortcomings, and provide practical reference for the intelligence of endurance sports training. At the same time, it also provides some useful suggestions for subsequent intelligent training strategies for all individuals.

2 Training load monitoring method

Monitoring training load aims to understand the athlete's response to the training plan, identify their adaptation to the training content, and evaluate fatigue and related recovery needs to reduce the risk of injury and illness for athletes. The main observed items of exercise load are external load and internal load, respectively. External load refers to the amount or intensity of exercise performed by athletes, and is an objective measure of the work completed by athletes during training or competition. Its evaluation is independent of external internal load. Common indicators for monitoring include power output, speed, acceleration, time-motion analysis, global positioning system parameters, etc. (Fox, Stanton, & Scanlan, 2018; Scanlan et al, 2014; Svilar et al, 2018). Intrinsic load refers to the physiological and psychological responses of athletes to exercise, which mainly include heart rate and conscious exercise intensity. Therefore, intrinsic load is the response of participants to the interaction of different physiological and environmental factors (Bourdon et al, 2017; Schwellnus et al, 2016).

2.1 Monitoring of external loads

The measurement of external load involves quantifying the training or competition performance of athletes, and its main measurement indicators include total training distance, training duration, single training distance, power output, speed, and number of repetitions of movements. For example, the training stress score (TSS) and acute/chronic workload ratio (ACWR), which can be calculated through bicycle power output, are widely used in triathlon endurance training platforms and virtual coaching platforms. It is not difficult to see that the concept of bicycle TSS has also been introduced in running training. The threshold speed of external load and the heart rate of internal load are used together as parameters to calculate the runner's stress score (rTSS). The data calculation includes heart rate, making rTSS not simply a parameter of external load (Field et al, 2019). Generally, athletes need to evaluate their adaptation to training and feedback on training effectiveness within a single week, especially when the peak load changes in the overall load, which can generate new stimuli and improve the athlete's physical fitness and performance. Therefore, when planning training sessions on a weekly basis, it is necessary to measure the training load within a few weeks to assist in allocating the ratio of acute and chronic training loads. ACWR is the ratio of acute load (within the last week) to chronic load (based on the average weekly training volume of the past four weeks). ACWR represents the current change in training load compared to the past. Its evaluation principle is that when the acute load for one week is lower than the chronic load for four weeks, a higher chronic load will have a protective effect on injury, allowing athletes to reduce the risk of injury when facing an increase in acute load. Data from intrinsic load (such as rTSS) and extrinsic load (such as training distance, TSS) can be used to evaluate（Table 1）.

Table 1: Statistical Table of External Load Evaluation Methods for Bicycle Power Output

Evaluation method	Principles and formulas	application characteristics
TSS[19-21] Sanders et al, 2016; Sanders et al, 2017; Van Erp et al, 2019	Formula 1: TSS=[(t) × NP × IF/(FTP) × 3600)] × There is no research literature to prove that this formula is an effective training load pointer. T is time; NP stands for normalized power; FTP is the functional threshold power; IF (intensity factor) is the intensity factor, which is the ratio of NP to FTP. Formula 2: TSS=h × IF2 × 100, h (hours) is the cycling time.	There is a strong dose-response relationship between TSS and the performance of well-trained competitive cyclists; Before the professional cycling season, TSS has a better load measurement value; IF will affect the amount of heat consumed, and it has a strong correlation with TSS.
ACWR[22-24] Lolli et al, 2019; Matos et al, 2020; Windt et al, 2019	Using traditional coupling and non coupling methods to estimate ACWR. The coupled ACWR formula is: acute load ÷ [0.25 * (sum of acute load+W2+W3+W4 training load)]; The non coupled ACWR formula is: acute load ÷ [0.3 * (total W2+W3+W4 training load)]. Acute load refers to the training load of the past week; W2, W3, and W4 respectively refer to the three weeks immediately preceding the most recent period. When the ACWR is between 0.80 and 1.30 (coupled) or 0.75-1.45 (uncoupled), it is the optimal range, reducing the risk of injury and exhibiting individual intrinsic differences and differences in exercise types. Internal load (such as training impulse TRIMP, rTSS) and external load (such as running volume/week) can be used for evaluation.	The pre competition reduction period will reduce chronic load, while increasing ACWR during the competition period is not suitable for predicting risk; It can be verified that the previously applied chronic load is sufficient to withstand acute loads.

Sports practice has shown that increasing training volume too quickly may increase the risk of injury for athletes. In order to maintain stable and efficient sports performance, athletes need to rely on long-term accumulation of high training load (chronic load). The use of ACWR quantification estimation formula can assist athletes in accumulating high training loads within a safer range. However, research has found that when using ACWR, attention should be paid to two aspects: firstly, when evaluating training load, it is not recommended to use ACWR alone. It must be analyzed and explained in conjunction with other information, such as training methods, absolute load changes, tolerance status, etc; Secondly, it is necessary to understand the impact of different calculation methods for ACWR. For example, including the pre competition reduction period in the calculation will reduce chronic load, while increasing ACWR during the competition period is not suitable for predicting risk.

2.2 Internal load monitoring

2.2.1 Applying subjective perceptual assessment

Table 2: Statistical Table of Relevant Principles and Formulas for Evaluating Training Load with Heart Rate

Evaluation method	Principles and formulas	application characteristics
Banister's TRIMP[20,25]	Banister's TRIMP=duration of exercise (min) * heart rate ratio * y (weighting factor); Heart rate ratio (HRR)=(average heart rate during exercise rest heart rate)/(maximum heart rate rest heart rate); Y=A * exHRR, e is a constant of 2.712; A is 0.64 for males and 0.86 for females; X is the gender coefficient, which is 1.92 for males and 1.67 for females	Not suitable for sports with high center rate fluctuations, such as interval training, road cycling competitions, mountain cycling, and running training.
TRIMPi[20,25]	Revise Banister's TRIMP by adjusting the weight factor y to yi=0.2445*$e^{3.411x}$, It can reflect the individual's blood lactate status during increasing load training.	Suitable for long-distance runners, can predict performance in long-distance races.
Edwards' TRIMP[20,25]	The sum obtained by adding the product of the time spent on 5 defined HR intervals and their weighting factors (1 to 5).	eTRIMP is suitable for training with large heart rate variability.
Lucia's TRIMP[20,25]	LuTRIMP=(HR interval 1 activity time * 1)+(HR interval 2 activity time * 2)+(HR interval 3 activity time * 3). Among them, HR interval 1: the interval below the aerobic threshold; HR interval 2: the interval between HR interval 1 and 3; HR interval 3: the interval above the anaerobic threshold.	The interval of three HR intervals is based on individual lactate threshold and the beginning of blood lactate accumulation. Suitable for training with large heart rate variability.
HRV[26] (Carrasco Carrasco-Poyatos et al, 2020)	Related to the vagus nerve. By using a heart rate band combined with scientifically validated smartphone application software for monitoring, HRV measurements can be obtained.	It depends on the individual's physical fitness level and training history. The measurement of heart rate variability after rest or exercise indicates both positive and negative responses to training adaptation.
EPOC[27] (Cunha et al, 2016)	EPOC (t) = f (EPOC (t-1, % VO_{2max}, Δt). EPOC (t) represents the estimated current EPOC; Δ T represents the duration of motion between two sampling points; EPOC (t-1) represents the EPOC of the first sampling point.	The EPOC of exercise involving larger muscle mass is higher, with running having a 37% higher EPOC than cycling; The same relative intensity of exercise, higher exercise heat consumption leads to higher EPOC.

There are two main methods for subjective perception assessment, namely the Rating of Perceived Exercise (RPE) and the Session Rating of Perceived Exercise (sRPE). RPE can monitor the physiological stress of athletes during exercise, and factors such as hormone changes, personality traits, and environment have a weak dose-response relationship with RPE. sRPE is scored on a scale of 0 to 10, and its product with the duration of training is used to represent the overall intensity, which is used as the intensity and fatigue monitoring for a single training or competition. Research has found that in endurance cycling training, RPE is closely related to heart rate during steady-state exercise and high-intensity interval training. Based on the fact that conscious exercise intensity is influenced by personal experience or tolerance, it is recommended to still refer to actual physiological measurements of intrinsic load data (Sanders et al, 2017; Windt & Gabbett, 2019). Currently, some training applications generally use REP.

2.2.2 Application of heart rate and heart rate variability assessment

The use of heart rate monitoring during exercise is based on the linear relationship between heart rate (HR) and stable oxygen consumption rate during exercise. At present, the intrinsic load principles of heart rate quantification in WD mainly include training impulse (TRIMP), heart rate variability (HRV), and post exercise oxygen consumption (EPOC). There are multiple calculation formulas for TRIMP, and Banister's TRIMP's training load quantification method uses training duration, average heart rate during training, and weighting factors for calculation, which can reflect the overall exercise volume during exercise (Sanders et al, 2017). Subsequent research has redefined the monitoring values for Banister's TRIMP based on the blind spot of using average heart rate, such as Lucia's TRIMP and TRIMPi ((Sanders et al, 2017; Windt & Gabbett, 2019). When monitoring bicycle training load, the total oxygen uptake of Banister's TRIMP (r=0.85) and Lucia's TRIMP (r=0.83) is highly correlated with the training load (Sanders et al, 2016). (See table 2)

Table 3: Related research on the application of heart rate variability

Author	Experimental subjects	Results
Flatt et al. (2018)	25 male college football players	HRV (1-minute ultra short term measurement) at rest during the 4-week spring training camp sitting position：1) After 20 hours of training, the LnRMSSDM of player b at the front line position still significantly decreased, while the receiver and defensive guard positions of player c have returned to the baseline value; 2) The higher the chronic training load, the lower the LnRMSSDCV.
Figueiredo et al. (2019)	16 U_{19} male football players	HRV (1-minute ultra short term measurement) during 4-week preseason training (1-week baseline period, 2-week overload period, and 1-week reduction period) when lying flat and resting: 1) LnRMSSDM and Yo Yo test performance decreased during the overload period, while LnRMSSDCV increased; 2) The HRV and exercise performance during the reduction period both returned to the baseline values.
Nakamura et al. (2020)	9 Top Male Five-a-side Football Players	HRV at rest during 4 weeks of pre-season training sitting posture: (1-minute ultra short term and 5-minute standard measurement)/After 4 weeks, LnRMSSDM increased, LnRMSSDCV decreased, and Yo Yo test performance increased.
Sekiguchi et al. (2021)	23 male college football players	HRV (5-minute standard measurement)/RMSSD increase during the first 2 days of 5 games in a season when lying flat and resting.
Plews et al(2013)	Elite endurance athletes	Moderate training load will increase aerobic fitness and HRV. When the training load approaches 100% of the individual's maximum training load, HRV will decrease and rebound during the training reduction period. Suggest conducting evaluation with a 7-day rolling record.
Plews et al 2017	Excellent leisure athletes	The reliability of WD measurement of HRV was verified, and the root mean square (rMSSD) index of the sum of squared differences between adjacent normal heartbeats obtained from smartphones and chest rate bands showed consistency with the HRV recorded on electrocardiograms.
da Silva et al (2019)	Healthy women aged 18-35	Determine training intensity through standardized cycle training or HRV. The HRV guided training group to perform more high-intensity interval training, resulting in a significant reduction in 5-kilometer running time, while the moderate intensity continuous training volume was negatively correlated with changes in 5-kilometer running time. The parasympathetic cardiac activity was only improved in the HRV

		group.
Javaloyes et al(2019	Male drivers with over 2 years training experience	HRV guided training group results: Peak power output, 2nd ventilation threshold power output, and 40 minute timed maximum output (all out time trial) significantly increased; Training well-trained cyclists in a short period of time may be more effective according to HRV planning than traditional cycle training.
Düking et al(2020)	Healthy runners of any age and grade	The application of HRV guidance training in 3000m and 5000m running timing, maximum load on bicycle ergometers, time to reach willpower exhaustion at maximum running speed, and sub maximum running parameters has shown significant improvements; Compared with traditional cycle training, HRV guided training can significantly improve running performance.

Note : HRV : heart rate variability ; LnRMSSD : natural logarithm of root mean square of successive differences ; LnRMSSDM : weekly mean LnRMSSD ; LnRMSSDCV : coefficient of variation of LnRMSSD ; Yo-YoIntermittent recovery test : Used to measure the ability of athletes to perform high-intensity repetitive runs in aerobic conditions. Frontline position: a position for athletes who require more muscle strength and muscle mass for body collisions but less aerobic fitness. Takeover and defensive guard positions: positions for players who require higher running speed and volume but lower physical resistance.

Table 3 shows:

In recent years, there has been an increasing amount of research on the changes in HRV of athletes before and after training and competition, as well as during rest periods. Among them, there has been more research on football players. Flatt et al. (2018) (Flatt et al, 2018) investigated the HRV changes of 25 male American football players at different positions during a 4-week spring training camp after 20 hours of training, as well as the relationship between training load and HRV. The results showed that there was a significant decrease in LnRMSSDM after 20 hours, despite requiring more muscle strength and muscle mass for body collisions, with less aerobic fitness for offensive and defensive linemen; The wide receiver and defensive back positions, which require higher running speed and volume but lower physical resistance, have returned to their baseline LnRMSSDM after 20 hours, and their LnRMSSDCV is lower compared to the linemen. Figueiredo et al. (Figueiredo et al, 2019) investigated the 4-week pre-season training of 16 U19 male football players. The results showed that during the overload period, the performance of LnRMSSDM and Yo-Yo intermittent recovery tests decreased, while LnRMSSDCV increased, indicating an increase in fatigue status of the players. Subsequently, during the reduction period, HRV and sports performance both returned to the baseline state. Nakamura et al. (Nakamura et al, 2020) investigated the changes in HRV of nine top male five a-side football players during the first four weeks of preseason training. The results showed that the increase in LnRMSSDM was relatively small when the training load increased during preseason training, but after four weeks, there was an increase in LnRMSSDM and a decrease in LnRMSSDCV. The increase in LnRMSSDCV was highly negatively correlated with the decrease in Yo-Yo test performance and the increase in perceived fatigue. Sekiguchi et al. (Sekiguchi et al, 2021) monitored the changes in RMSSD during the season for 23 male college football players, and found that the RMSSD value increased as the season progressed.

In the field of endurance training, the prospect of HRV providing real-time monitoring for sports training is also worth paying attention to. A study by Plews et al (2013) on elite endurance athletes found that moderate training load increases aerobic fitness and HRV. When the training load approaches 100% of an individual's maximum training load, HRV decreases and rebounds during the training reduction period. A study by Plews et al (2017) on excellent leisure athletes found that the reliability of WD measurement of HRV, the root mean square (rMSSD) index of the sum of squared differences between adjacent normal heartbeats obtained from smartphones and chest rate bands, and the level of consistency between HRV recorded on electrocardiograms were consistent. Da Silva et al (2019) found in a study of healthy women aged 18-35 that training intensity was determined by standardized cycle training or HRV. The 5-kilometer running time was significantly shortened, while moderate intensity continuous training was negatively correlated with changes in 5-kilometer running time. Parasympathetic cardiac activity was only improved in the HRV group. Javaloyes et al. (2019) found in their study on male drivers with personalized training experience that HRV planning may be more effective than traditional cycle training, such as monitoring the peak power output of cyclists, the second ventilation threshold power output, and the all-out time trial of a 40 minute time. Düking et al (2020) found in their study on healthy runners that compared to traditional cycle training, HRV guided training has a significant effect on improving 3000m and 5000m running performance, such as improving maximum load on bicycle ergometers, maximum running speed, willpower exhaustion time, and sub maximum running parameters.

2.2.3 Application self-report assessment

At present, the most common method for monitoring high-performance exercise fatigue is self-report questionnaires. However, the vast majority of participants question the scientific validity of this method, citing its wide range of issues, time-consuming nature, and lack of exercise specificity. However, perceived muscle soreness, sleep, and perceived fatigue as important indicators of recovery cannot be ignored (Garrett et al, 2023). Although self-report is not a physiological measurement, its principle and application focus are of great importance in sports psychology and management. Saw et al. (2015) found that self-reported athlete management can identify adverse reactions, achieve real-time intervention, promote communication and athlete self-management, confirm the appropriateness of daily and long-term coaching methods, and better understand how to prepare for training and competition. The current execution status of self reporting in training applications mostly adopts open fields, allowing athletes to fill them out on their own. Coaches can formulate projects, and athletes can reply to the fields. At the same time, athletes can be encouraged to keep records of training diaries. To maintain the effectiveness and positive outcomes of the self-report monitoring training method, it is necessary to carefully follow the four steps in sequence when applying it：

1) Record Data - Record information related to training execution (sleep, nutrition, recovery and training details, any unusual reactions) to confirm whether athletes are preparing as expected and achieving the expected training pressure. When athletes are unwilling to express themselves face-to-face, discursive descriptions are in some cases seeking help. Subjective well-being can indicate the extent to which athletes cope with stress, determining training stimuli and adaptive responses. Improving confidence through reviewing accurate records。

2) Review data - can serve as an early warning system, identify potential issues and enable proactive methods to solve them, understand factors that affect performance outside of training, and assess the individual's ability and limitations in injury status.

3) Contextualization - contextualize unusual reactions or comments into hints for athletes to invite and discuss, providing care and communication.
4) Action - Coach feedback is the core value and needs to be timely and easy to understand. When any unfavorable situation is found among athletes, relevant staff should be referred for assistance to increase their sense of responsibility and improve self-discipline.

3 Systematic data management and virtual reality (VR) sports platform

With the popularization of the Internet and smartphones, WD has become a new opportunity to motivate people to engage in sports training. After the intervention of WD, sports software and hardware, and the Internet of Things in sports training, the amount of data that technology can provide continues to increase. Applications integrate and present data and analysis results through charts and colors, providing easy to read interfaces and data aggregation functions to the best of their ability. With limited funding considerations, athletes and coaches can obtain basic training management functions through WD and its free applications. The powerful functions of the IoT can connect hardware WD, heart rate bands, bicycle power devices, and intelligent training devices with software mixed reality sports platforms, WD applications, and sports community platforms, automatically sharing data at the end of training, generating meaningful feedback functions, and executing system method management.

3.1 Training content planning and effectiveness evaluation

Using an application to upload training schedules and routes to WD, athletes do not need to memorize intricate details or constantly check their phones. WD will actively prompt and start the timing of the next training step based on the order and time of the training schedule, and remind whether the pace has reached the set range. It is also possible to view the map and direction on the surface, allowing athletes to focus more on their body movements. For example, using the Garmin watch, its application provides multiple virtual running coaches to choose from. Based on the set goals, training days, and competition dates, it helps athletes plan training schedules, evaluate them based on the training related data generated by athletes during training, and adjust and design subsequent training schedules. By comparing the pace and step frequency of running, stepping power (wattage) and step frequency, and climbing data, potential mechanical injury risk factors can be observed and discovered, such as excessive stepping or choosing too heavy gear ratios, which may increase the burden on joints. In addition, the mileage of shoes and other equipment used can be monitored to determine timely replacement, and important information that cannot be displayed through open fields can be recorded.

3.2 Record and analyze exercise performance and load data

The WD application utilizes training load and maximum oxygen uptake to evaluate and prompt training effectiveness. For example, effective training, poor performance, peak state, overtraining, maintenance, recovery, and cessation of training, and relevant suggestions (such as insufficient reminder intensity, or attention to recovery and rest) can be proposed. The training plan can also be adjusted by observing changes over the past month or longer. You can also use the proportion of heart rate interval to understand the proportion of different intensities in the current training; Use the detected lactate threshold and FTP to determine whether the training intensity and quantity are appropriate.

3.3 Integrate health-related data

Systematic data management and VR exercise platforms can estimate the amount of calories consumed during exercise, daily basal metabolism, and total calorie consumption through calorie consumption, which helps plan diet and supply, as well as weight management; By recording the maximum heart rate and resting heart rate, it helps to understand the recovery state and plan training intensity; By relying on sleep statistics, it is possible to record sleep time and past sleep hours (such as sleep hours per week), evaluate whether athletes have insufficient sleep, need to strengthen recovery and rest; Menstrual cycle reminders and records can also be used to help female athletes understand their own physical and emotional symptoms, the pressure of training and competition, and the correlation and interaction with changes in the menstrual cycle, and can timely adjust the schedule in advance to obtain appropriate rest. The platform system can be guided by AI and human coaches through face-to-face, communication technology, virtual environment, IoT, etc. At present, the operating system of online endurance sports platforms mainly includes four levels: recording activities, VR, load assessment, and AI virtual coaches (Boratto, Carta, Mulas, & Pilloni, 2017).

Table 4: Comparison of Sample Functions of Online Endurance Sports Platforms

Platform Name	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Strava Record Activity Platform	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Zwift VR Training Platform(ZWVRTP)	Yes	No	No	No	Yes	Yes	No	Yes	No	Yes	Yes
TrainingPeaks Load assessment platform	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Taday's Plan AI Virtual Coach Platform	yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No

(1) IoT functionality; (2) Mobile GPS recording activities; (3) Real person coach sharing and interaction Athlete Management System Provide training plans; (6) Training plan category; (7) Assess training load Statistical training volume; (9) Perceived intensity assessment Open Record Community website features

Table 4 shows：

1）Record activities. In online communities, the desire for personalization and ideal self-expression is an important attraction of online social fitness networks (OSFNs), originating from a wider range of social media websites such as Instagram and Facebook. Taking Strava as an example, using social networking sites as a guide, managing personal image through recording activities can also improve exercise self-efficacy through alternative experiences, sparking a wave of endurance training and sports, attracting attention from sports psychology and big data research in the past five years. From research on Strava, it can be inferred that OSFNs aim to explore the impact of the motivational empowerment framework of information and communication technology (ICT) on athlete motivation empowerment and discourse practice (Rivers,2020).

2）VR. VR has shown enormous application prospects in digital sports training. For example, a bicycle intelligent trainer combined with the ZWVRTP application continuously adjusts resistance to simulate terrain elevation fluctuations, and intervenes the program in changes in traction airflow and power. According to Irwin et al. (2012), the duration of training with more capable training partners is longer, resulting in a 102% improvement in individual training performance. Using ZWVRTP for training, athletes do not need to invite friends and companions in real life. The platform provides virtual speeders to lead global users in easily accessible international team cycling. Athletes can choose a specific thrust ratio (watt/kg body weight) based on the intensity of their individual training to enjoy virtual speedometer leading services. The ZWVRTP program, with its special design of a fixed thrust ratio, can weaken the difference in individual absolute physical fitness among athletes, allowing them to schedule training sessions with athletes with better absolute physical fitness who are difficult to ride side by side in reality, generating team motivation, improving individual sports performance, and eliminating negative environmental factors (such as rainy days, continuous cycling due to traffic interruptions, etc.). It is widely favored by cyclists and trirail athletes. In addition, VR can also be applied to long-distance running training. In the future, when facing factors such as weather, holidays, and time arrangements that make it difficult to perform outdoor team training, athletes only need to bring their phones and WD to schools or nearby gyms to participate in online team training with their teammates.

3）Assess the load. At present, free applications in WD, such as Garmin Connect, can provide assessment of simple training load for athletes to refer to. A paid sports platform that specifically provides training load analysis and training management, such as Training Peaks, can connect athlete and coach accounts and WD through IoT, connecting data transmission and sharing. Coaches can upload course schedules to the athlete end and monitor the training effectiveness of athletes. Both parties can leave messages, interact, and give feedback. However, athletes or coaches must have the ability to interpret the professional terms used in various training loads on the platform in order to understand the meaning represented by the analysis charts provided by the application and apply them to personnel planning and training schedules. Therefore, their use still relies on real person expertise.

4）AI virtual coach (see Table 5). Virtual coaches planned by AI can efficiently and systematically manage sports training data. It can be divided into three types (Hultgren, Palmer, & O'Riordan, 2016): virtual self-learning, AI coaching, and mixed virtual coaching. Westmattelmann et al (2021) explained that mixed-reality (MR) is the area between two points in a purely real world environment and a computer generated VR environment, MR technology has been applied to improve training quality, while motion VR applications are defined as using computers to generate motion related content Athletes interact with VR environments, allowing for repetitive manipulation and practice of specific skills for evaluation and feedback。Users mainly focus on data analysis and tracking weekly training progress and progress, while whether friends use it is not a factor that users consider; Gamification of virtual reality applications is key to changing user behavior, and real-time data feedback is one of the most fundamental elements of gamification (Westmattelmann et al, 2021; Tóth & Lógó,2018).

In short, virtual sports platforms use Bluetooth and networks from mobile phones or computers to integrate computer applications, training hardware, and sports platforms into one world. Through the Internet of Things, athletes are brought into virtual space and data is shared between programs. Jiajun et al. (2020) pointed out that the success or failure of sports services, in addition to convenience, ultimately needs to be defined by people. Smart technology and the sports and fitness industry consider the human needs of athletes, attach importance to contact and interaction, meet customized needs, and maintain the warmth of sports services. Arndt et al.'s study (2018) pointed out that there are four main factors in the application of VR sports, including task, user, VR environment, and non VR environment. When endurance athletes such as rowing, treadmill running, and cycling are brought into virtual reality and explored to improve training performance (such as time, power, etc.), the training distance and power output of athletes show an increase in sports performance, The use of virtual reality has a positive impact on situational, emotional, temporal perception (easily forgetting time), and distraction.

Table 5: Research on Mixed reality sports platform

Author	Research object/research results
Irwin et al (2012)	The exercise performance of women aged 20.54 ± 1.86 years/under the cooperative condition of training with another person improved by 49% compared to individual training performance. The duration of training with more capable training partners was longer, significantly higher than under collaborative conditions, and improved by 102% compared to individual training performance.
Nunes et al (2014)	22 to 52 year old users/can generate competitiveness in virtual environments, with 88% of virtual running users feeling the need to surpass others or opponents and motivate them to use. The subjects want to compete with other real users, rather than virtual characters. Immersing virtual environments can increase motivation and generate interest in regular use. The main sources of stimulation in virtual environments are the characters representing themselves in the game (40%) and the virtual immersion in the game (36%).
Westmattelmann et al (2021)	The UCI German professional team and non professional athlete users, as well as non users/key features, promote interaction between users through group cycling in a shared space, generating social and competitive communication. Urbanization, terrain, and weather seasons are prerequisites for use. Competitive cyclists mainly use off season breaks. The key reason why non users are unwilling to use bicycles is that they are used for outdoor sports.

4 Conclusion

1）The powerful functions of the IoT can connect multiple parties such as WD, heart rate bands, bicycle power devices, intelligent training device applications, and sports community platforms, automatically sharing data at the end of training, generating meaningful feedback functions, and executing system method management;

2）The four levels of online virtual sports platforms jointly executed by AI and human coaches (recording activities, virtual reality, load assessment, AI virtual coaches) all reflect the close integration of modern sports and the Internet of Things, supporting direct interaction between athletes and human coaches, generating different forms of motivation and participation for athletes, and having the function of promoting training motivation, improving sports performance, and maintaining training quality; The partnership between online virtual and live coaches has better benefits in promoting athletes to complete training programs；

3）HR and HRV are important indicators for objectively evaluating the intrinsic load of sports training, and their derived indicators such as TRIMP, EPOC, RMSSD, RMSSDM, RMSSDCV, LnRMSSDM, LnRMSSDCV, etc. have reference value for providing real-time adjustment of training strategies on the day of training, which can promote and improve maximum training efficiency. However, HRV planning may be more effective than traditional cycle training

5 Recommendation

1）Intelligent WD can monitor exercise load in real-time and improve training efficiency. However, when evaluating training load, it is not recommended to use ACWR alone. It must be combined with other information, such as comprehensive training methods, absolute load changes, tolerance status, internal health, etc., to develop the most favorable training plan for athletes；

2）HR and HRV are the most convenient physiological indicators used to evaluate training intensity in various sports. As optical heart rate is influenced by factors such as tattoos on the skin and sensor contact surface, sweat, whether it is worn or not, or external light sources received by the sensor, how to improve the measurement accuracy of optical heart rate in the future will be a major issue in WD development；

3）How to combine personal experience with WD simulation to find the most suitable nutrition supply strategy is another challenge in improving exercise performance. It is recommended to evaluate the current exercise intensity based on the intensity of the preset training schedule or the heart rate during training, and then combine relevant empirical research on current exercise physiology and athlete weight to develop the supply strategy function of WD。

4）The existing intelligent training and sports platform training systems mainly serve the performance of competitive sports. With the application of intelligent sports training big data, the future should develop towards a higher level of service in the sports technology industry, and construct an optimized environment for the national fitness industry service, thereby touching on the establishment of sports clubs, school sports teaching, and school team training.

Disclosure

Author's contribution

This article is designed and written by Tingran Zhang and Jiong Luo. Mufan Zhang is responsible for literature collection and organization. Meanwhile, Luo Jiong is the project manager and has approved the author and corresponding author of this study.

All authors have read and agreed with the published version of the manuscript.

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