

Real-time Dynamic Data-driven Wearable Devices in Sports Training

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Wearable technology has become indispensable in modern sports training, enabling the real-time monitoring of biometric data and enhancing athlete performance through dynamic, data-driven feedback. In this study, 120 athletes from football, rugby, and swimming participated in a 12-week training program using advanced wearable devices, including Garmin Forerunner, Fitbit Charge 6, ActiGraph GTX3+, and Polar Team2 Pro. The survey results revealed high satisfaction with the devices: usability and comfort [mean score of 4.00, standard deviation (*SD*) of 0.46], data accuracy and reliability (mean score of 4.05, *SD* of 0.42), impact on training and performance (mean score of 4.03, *SD* of 0.52), and overall satisfaction (mean score of 4.01, *SD* of 0.46). Despite nonsignificant correlations among these variables, the participants reported substantial improvements in sprint time, endurance, and recovery rate. Case studies demonstrated performance gains of 8–12% in soccer, a 23% reduction in milestone achievement time in swimming, and a reduced injury downtime in rugby. The results showed the contribution of advanced sensor technology, such as photoplethysmography, electrocardiogram, accelerometers, and GPS modules, in enabling precise, adaptive training programs. The integration of machine learning and mobile applications enhances personalization, injury prevention, and tactical analysis. This research underscores the pivotal role of sensor development in shaping the future of sports training, where wearable devices provide reliable, actionable insights for athletes and coaches.

1. Introduction

Wearable technology has revolutionized sports training by enabling coaches and athletes to seamlessly collect, analyze, and act on real-time data, enhancing performance and decision-making. Wearable technology enables the continuous monitoring of biometric data during exercise and sports activities. This technology helps athletes stay in peak condition, minimizes

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the risk of injuries, and optimizes training efficiency.⁽¹⁾ Wearable devices track and analyze changes in an athlete's heart rate, movements, and energy levels, providing basic data for performance optimization (Fig. 1). Real-time scientific data empower coaches and athletes to fine-tune training programs and develop strategies, which were previously limited with traditional methods.⁽²⁾

Athletes need to continuously enhance their performance, while coaches must monitor their health. Even marginal improvements in training enable athletes to secure a competitive edge. Wearable devices are used to monitor key metrics, such as heart rate variability (HRV), blood oxygen level, sleep quality, and others, which provide data to enhance training effectiveness and athletes' well-being.⁽³⁾ For instance, the early detection of fatigue allows timely interventions to prevent recurring injuries and foster rapid recovery. Athletes and fitness enthusiasts are using wearable devices to monitor and optimize their performance.⁽⁴⁾

Advanced sensor technology, empowered by advanced data transmission and analysis over wireless networks, has significantly driven the rapid development of wearable devices. In the early stage, fitness trackers could only count steps and monitor heart rate, but recent ones capture various biometric signals in real time.⁽⁵⁾ Integrating cloud computing and AI has further contributed to the development of wearable devices, enabling the collection and analysis of vast amounts of data to identify factors contributing to performance enhancement or injuries.⁽⁶⁾ By processing numerous data points at high frequencies, instant training feedback is provided, which helps coaches monitor athletes' progress over time. These advancements have positioned wearable devices as an essential tool in sports.

Given the rapid advancements in sensor technology and wearable devices, it becomes essential to optimize training programs to achieve improved results with real-time, dynamic, and data-driven analytics. Therefore, we evaluated the effect of wearable devices in sports



Fig. 1. (Color online) Diverse wearable devices.

training. We explored how feedback from these devices is used to personalize training programs, prevent potential injuries, and support rehabilitation. The results of this study contribute to enhancing athletes' performance and enabling coaches and sports organizations to use the technology effectively. Wearable devices with advanced sensor technology also enable training programs to be tailored to each athlete based on real-time data analytics.

2. Technology Review

2.1 Real-time monitoring

Advanced wearable technology has enabled the monitoring of athletes' biometrics in real time and helped coaches guide training and athletes improve performance. Wearable devices are equipped with advanced sensors to monitor biometric statuses such as HRV, blood oxygen level, skin temperature, the content of sweat, and electrocardiogram (ECG) (Fig. 2). Whoop Strap 4.0 and Apple Watch Series 9 employ photoplethysmography and advanced sensors to collect biometric data noninvasively⁽⁷⁾ and help athletes check their performance. The data enable athletes to assess their hydration and fatigue levels, and coaches monitor the athlete's health and performance to understand readiness and optimal condition.

Advanced sensor technology enhances biometric monitoring capabilities. Hexoskin Smart Shirt and Biostrap EVO Bracelet integrate electrodes and high-precision accelerometers to monitor respiratory rate, tidal volume, movement patterns, and core cardiovascular metrics.⁽⁹⁾ By combining multiple data streams, these wearable devices enable the early detection of fatigue, dehydration, and abnormal stress responses. Moreover, they are easy and comfortable to use as they are light and made of breathable materials in ergonomic structures to minimize movement interference. Wearable devices enable consistent usage, making training and competition efficient and seamless for athletes.

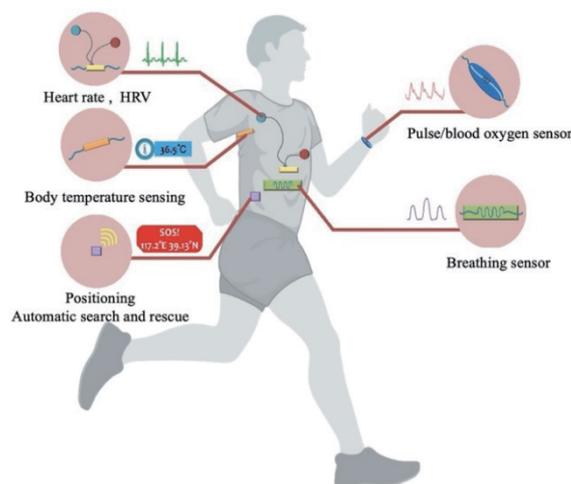


Fig. 2. (Color online) Wearable sensors for biometric measurement.⁽⁸⁾

2.2 Machine learning (ML) algorithms for data interpretation

The vast amount and complexity of data collected by wearable devices require advanced analytical methods. Therefore, ML algorithms are widely used to extract important features.⁽¹⁰⁾ Supervised and unsupervised ML models are widely employed to identify trends, predict performance outcomes, and provide early warning signs of injury or overtraining. Convolutional and recurrent neural networks have been used to analyze time-series data, including inertial measurement units and heart rate monitors for movement classification, energy estimation, and fatigue prediction.

ML in sports also enables personalized coaching and post-workout recovery optimization. By analyzing an athlete's historical and real-time performance, ML algorithms generate individualized feedback tailored to their specific physiology and training records, optimizing workload management and minimizing injury risks. Firstbeat and Catapult leverage proprietary algorithms to provide quantitative feedback on training load, recovery needs, and on-field exertion levels, which helps coaches and athletes adjust training strategies. Such feedback enables athletes and coaches to determine workout intensity, exercise selection, and recovery timing, ultimately enhancing performance while safeguarding health.

As ML models continue to evolve with expanding datasets and powerful computing resources, more precise and adaptive solutions are expected to keep revolutionizing sports training and performance monitoring.

2.3 Mobile applications

Recently, wearable devices have been connected to mobile applications to collect data, provide feedback, and communicate with other devices. Garmin Connect, Strava, and Polar Flow aggregate data from various fitness trackers and smartwatches, presenting them in graphs that highlight progress, metrics, and personalized feedback. These platforms incorporate goal-setting and social sharing, helping athletes stay motivated and engaged. Real-time notifications and alerts sent to smartphones or smartwatches show present hydration levels, recovery status, and performance trends, allowing athletes to quickly adjust their training or competition.

The integration of mobile applications and wearable devices has enabled remote coaching and medical monitoring, allowing athletes to receive expert guidance regardless of location. Coaches and sports scientists review real-time performance data and analyze historical trends to offer advice through secure messaging or video calls. This capability ensures continuous progress despite challenges when in-person training is not available.⁽¹¹⁾ Many mobile applications incorporate AI-powered chatbots and digital assistants to provide tailored recommendations, answer user queries, and support athletes in training and recovery. The integration of wearable devices and mobile applications enhances accessibility, delivering personalized guidance precisely when athletes need it.

2.4 Personalized training with adaptive programs

One of the most transformative advancements in modern wearable devices is their ability to provide personalized training and adaptive programs. The devices are used to continuously monitor an athlete's movements and biometrics, enabling real-time adjustments to workout plans and rehabilitation schedules based on individual needs. TrainAsONE and AI Endurance analyze the data collected from fitness trackers to keep training aligned with an athlete's actual performance and readiness.⁽¹²⁾ The algorithms analyze sleep patterns, heart rate, injuries, and environmental conditions, and provide results to make customized training plans.

The benefits of adaptive training are substantial. Athletes receive tailored guidance that enhances performance while mitigating risks of overtraining and injury. Athlete Fresh 2.0 equips coaches with in-depth analytics to design effective long-term monitoring programs. Such training systems accommodate unexpected disruptions, such as illness, travel, or scheduling changes, to ensure training consistency. This adaptability is important, where even marginal gains are important to obtain the outcome.⁽³⁾ As wearable devices continue to advance, corresponding training programs become increasingly precise, allowing athletes to personalize their training.

Real-time biometric tracking, advanced data analysis, and personalized feedback play a crucial role in enhancing athletic performance and safety. These technologies enable the early detection of dehydration, overheating, and abnormal heart activity to prevent injuries.⁽²⁾ The continuous monitoring of body temperature and sodium level in sweat contributes to the risk reduction of heat-related illnesses in training or competition. Real-time biomechanical assessments, such as ground reaction forces and joint movements, help identify and correct inappropriate movement patterns that might lead to musculoskeletal injuries.

Integrating wearable device data into medical systems and sports medicine platforms allows healthcare professionals to monitor an athlete's long-term health and recovery. This enables the implementation of individualized rehabilitation programs for effective recovery and minimizing downtime from training or competition. Wearable devices are also used to detect injuries such as concussions, accelerate recovery progress, and reduce potential health risks.⁽⁴⁾ As more athletes and teams are adopting such systems, wearable devices and sensor technology are profoundly enhancing the athlete's well-being.

3. Case Studies

3.1 SV Fügen football club

The SV Fügen football club has used the Firstbeat Sports solution for their training to enhance team performance. The solution consisted of athlete sensors, a mobile application, and a coach-specific dashboard. HRV, training intensity, and recovery time were monitored using sensors. The collected data were analyzed using advanced cloud-based tools, and the results were displayed on the application and dashboard.⁽¹¹⁾ The solution provided coaches and athletes with real-time data and enabled data-based decision-making. The club adopted the solution to

maintain consistent performance as the solution monitored and analyzed the biometric data of the athletes and optimized each training program. After using the solution for a year, training sessions became more efficient than before, and athletes' well-being improved. With HRV and recovery data, personalized training plans were offered to ensure athletes' optimal health condition. On the basis of fatigue and injury risk predictions, coaches adjusted workloads to minimize the risk of injury and sustain preparedness for competitions.⁽¹³⁾ Access to performance data motivated athletes, helping them monitor changes in health and readiness. Firstbeat's detailed biometric data enabled athletes to understand their conditions, leading to informed decisions and a stronger, more resilient team training and performance.

SV Fügen's successful implementation of the solution demonstrates the role of wearable devices in sports. Active biometric monitoring improved performance and prevented injuries, proving the benefit of using advanced technology in sports. Wearable devices enable effective coaching and data-driven training. Related technology has become essential for enhanced outcomes through efficient training, which is not available with traditional methods.

3.2 GPS-embedded vest in soccer

Many elite soccer teams are using GPS-embedded vests to monitor their athlete's activity in training and matches. Equipped with accelerometers, gyroscopes, and GPS modules, the vests are worn to continuously track each athlete's on-pitch position, running speed, and exertion levels throughout a game. The vests allow coaches to observe performance indicators and deviations from a player's typical patterns. A significant decrease in sprint speed or overall running distance, for instance, signals fatigue or an impending injury. Such data help coaches adjust tactics or decide on athlete substitutions. The collected data are analyzed using mathematical models to identify statistically significant variations and notify coaching staff for timely intervention. Beyond individual monitoring, GPS-embedded vests offer data on dynamics and tactical execution. By analyzing the collective movement of the team, coaches can refine formations, optimize spacing between players, and assess the effectiveness of their strategies. For example, the defensive line's speed and interplayer spacing are measured to evaluate the team's structural integrity during critical phases of a game. Such information was unobtainable with traditional methods, which relied on subjective observation and post-match reviews. The availability of real-time data enables informed decisions before and during matches.

The widespread adoption of GPS technology in wearable devices enhances team performance and reduces the risk of athlete injuries. Such systems contributed to an 8 to 12% improvement in performance metrics within a year.⁽¹⁴⁾ This improvement is attributed to the optimization of high-intensity running distances and the reduction of nonfunctional overreaching through precise load monitoring. The ability to identify early signs of fatigue or improper biomechanics has contributed to injury rate reduction. Wearable devices have become indispensable in modern sports, providing a data-driven approach to training and in-game strategy.

3.3 Biomechanical analysis in rugby

Wearable devices also significantly assist strategic planning and injury prevention in professional rugby. To monitor biomechanic data in training and matches, inertial measurement units (IMUs) and advanced positioning systems are used. Such devices are used to monitor acceleration, joint loading, and movement symmetry, and the data are used to optimize performance and reduce injury risk. IMU exceeding 15% on a limb in force imbalance signals an increased likelihood of injury. By regularly monitoring these metrics, coaches and medical staff can identify high-risk athletes and address imbalances that might result in injuries. In rugby, wearable devices significantly assist strategic planning and injury prevention. The regular monitoring of movement symmetry and joint loading has been shown to reduce injury-related downtime, which indirectly enhances team performance by ensuring player availability.⁽¹⁵⁾ Algorithms analyze player and ball movement to assess defensive effectiveness and reaction speed. Real-time data on defensive line pace, formation, and individual player responses enable coaches to promptly improve their strategy. Wearable devices, sensor data, and analytics enable data-driven decisions based on objective performance metrics to enhance performance.

3.4 Personalized training in swimming

Swimmers can significantly improve their technique and results by using advanced sensors. These sensors are worn on the wrist or swim cap to monitor stroke count, length, and subtle technique variations in training. Collected biometric and biomechanical data are used by coaches to determine optimal training zones and tailor workouts to each swimmer. Real-time feedback enables swimmers to instantly adjust their form, boosting speed and preventing overuse injuries. Monitoring stroke mechanics and exertion permits immediate training adjustments when deviations occur. Wearable devices are used in training program design in swimming. Coaches personalize training programs through precise assessments to improve performance. Olympic training centers in China, for example, have shown a 23% reduction in time to reach preset milestones, increased workout intensity by 15%, and reduced recovery time by 20%, highlighting the impact of wearable devices on swimming.⁽¹⁶⁾ By adopting wearable devices, swimmers and coaches enhance engagement and confidence. Prominent improvements through instant feedback motivate swimmers to use wearable devices.

4. Materials and Methods

4.1 Wearable devices

In this study, wearable devices were used to monitor participants' health and training activities. Garmin Forerunner watches tracked heart rate, speed, and total distance, whereas Fitbit Charge 6 and Keep B4 fitness trackers recorded step count, calories burned, and sleep patterns. ActiGraph GTX3+ and Polar Team2 Pro were used to measure motion intensity, acceleration, and deceleration using their built-in accelerometers, and HRV, respectively.⁽¹⁷⁾

Chest straps were employed for heart monitoring, whereas accelerometers and GPS units were positioned at the wrist or waist (Fig. 3). These devices were chosen for their accuracy, reliability, and widespread use.⁽¹⁸⁾ To ensure data precision, all devices were used according to technical guidelines. We used various devices to accurately assess athletes' health and performance.

A total of 120 athletes from diverse sporting backgrounds, including football, rugby, and swimming, were recruited for this study. The participants were randomly selected using a stratified sampling method to include representative data from football, rugby, and swimming sports. To ensure the robustness of the survey data, all 120 participants participated in a 12-week training program where they utilized the wearable devices described in Table 1. Every participant had significant, long-term interaction with the technology before completing the evaluation survey. Their performance improvements were monitored longitudinally, comparing individual growth against baseline metrics monitored at the start of the 12 weeks.⁽²⁰⁾

4.2 Data collection and analysis

We recruited 120 athletes. A structured questionnaire survey was administered after the experiment. A five-point Likert scale was adopted to evaluate usability, accuracy, comfort,

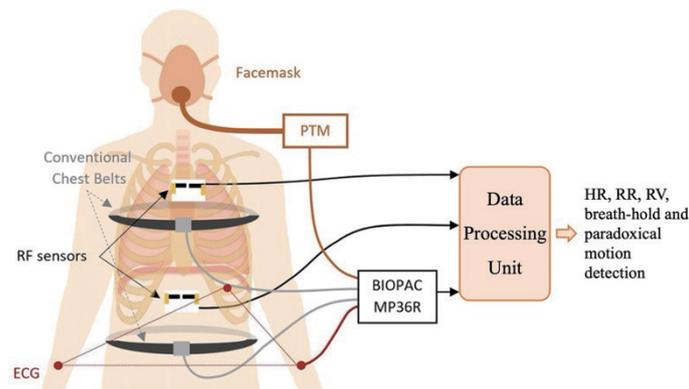


Fig. 3. (Color online) Remote sensing of biometric data using wearable devices.⁽¹⁹⁾ (HR: heart rate, RR: respiratory rate, RV: residual volume, RF: radiofrequency, PTM: personal therapy manager, and BIOPAC MP36R: 4-channel data acquisition unit to record physiological signals).

Table 1
Specifications of wearable devices used in the study.

Device	Sensor	Dimension (mm)	Data transmission
Garmin Forerunner ⁽²¹⁾	GPS (position and speed), HR, photoplethysmography (PPG)	42 × 42 × 11	Bluetooth/adaptive network topology+
Fitbit Charge 6 ⁽²²⁾	PPG, HR, ECG, 3-axis accelerometer	36 × 23 × 11	Bluetooth low energy
ActiGraph GT3X+ ⁽²³⁾	Micro-electro-mechanical systems, accelerometer (raw acceleration)	46 × 33 × 15	USB, Bluetooth
Polar Team2 Pro ⁽²⁴⁾	ECG-based heart rate (chest strap)	62 × 34 × 10	2.4 GHz proprietary

performance impact, and overall satisfaction with wearable devices. Survey responses were coded and analyzed to identify trends and differences using the Statistical Package for the Social Sciences. Performance improvements, including sprint time, endurance capacity, and recovery rate, were compared alongside subjective measures of usability and satisfaction. By integrating biometric outcomes with athlete perceptions, the analysis provided a comprehensive evaluation of wearable devices in sports training.

To examine the impact of wearable devices on user perceptions, multivariate analysis of variance (MANOVA) was employed. This analysis tested the simultaneous effects of usability and comfort, data accuracy and reliability, impact on training and performance, and user experience and satisfaction. Four standard multivariate statistics were reported: Wilks' Lambda (λ), Pillai's Trace, Hotelling's Trace, and Roy's Largest Root. Wilks' Lambda represents the proportion of unexplained variance, Pillai's Trace is robust to assumption violations and ideal for sports survey data, Hotelling's Trace compares groups across multiple dependent variables, and Roy's Largest Root focuses on the maximum eigenvalue as an upper bound for the F -statistic.⁽²⁵⁾ The significance of these metrics confirmed that differences in athlete perceptions across the 12-week study were significantly affected by the integration of wearable technology.⁽²⁶⁾

5. Results and Discussion

5.1 Results

The results of the study consistently demonstrate that participants expressed strong positive attitudes toward wearable devices across all evaluated dimensions (Table 1). The results in Figs. 4–7 presented the collective feedback of the total cohort ($n = 120$). Because all participants were active users of the sensors, the data provide a high-confidence assessment of the technology's practical application in real-world sports environments. Usability and comfort showed a mean score of 4.00, with most responses clustering around this value, indicating that athletes found the devices easy to use and comfortable to wear during training (Fig. 5). Data accuracy and reliability scored slightly higher at 4.05, with the distribution peaking at 4.00 and showing a strong concentration of responses between 3.50 and 4.50, which highlights that participants valued the precision and dependability of the devices (Fig. 6). The impact on training and performance was assessed positively, with a mean of 4.03 and the highest frequency at 4.00, suggesting that athletes perceived wearable devices as beneficial for improving their training outcomes, even though the slightly wider spread of scores reflected some variation in perceived impact (Fig. 7). Finally, user experience and satisfaction had a mean score of 4.01, again with the highest frequency at 4.00, confirming that participants were generally satisfied with the devices and found them practical in training contexts (Fig. 8).

The results reveal the following pattern: Wearable devices were regarded as comfortable, accurate, impactful, and satisfying, with all mean scores exceeding 4.0 and relatively small standard deviations (SDs) indicating a broad consensus among participants (Table 2). The convergence of results across usability, reliability, performance impact, and satisfaction underscores that wearable devices are not only technically effective but also well received by athletes, making them a valuable tool for enhancing training and performance.

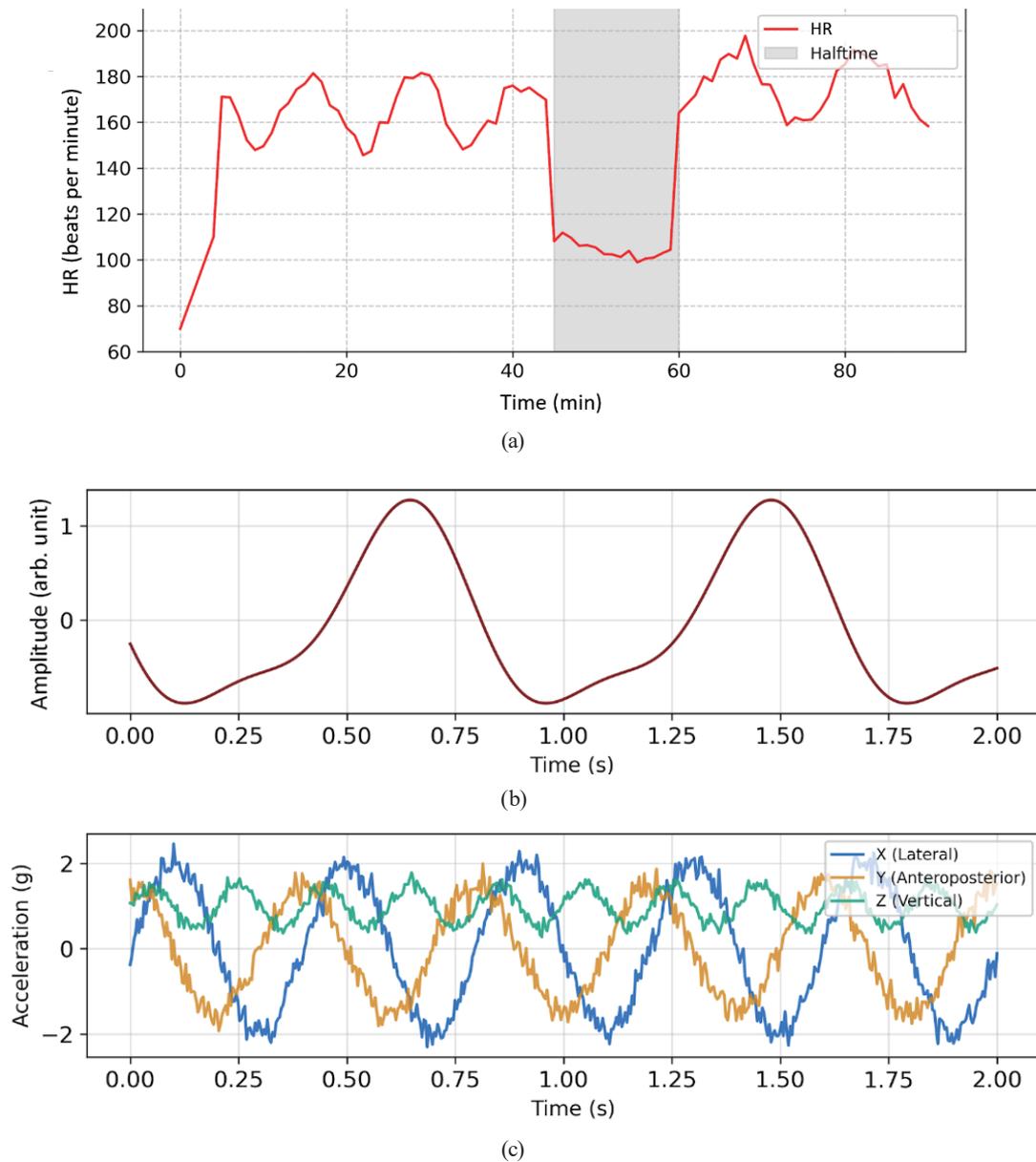


Fig. 4. (Color online) Representative signals obtained from athlete during 90 min training: (a) HR, (b) PPG (arb. unit), and (c) three-axis accelerometer signal.

Table 3 presents the Pearson correlation coefficients among usability and comfort, data accuracy and reliability, impact on training and performance, and user experience and satisfaction. None of the correlations showed statistical significance at $p = 0.05$. The correlation coefficients between usability and comfort and data accuracy and reliability ($r = -0.057$, $p = 0.534$), usability and comfort and impact on training and performance ($r = -0.064$, $p = 0.490$), and usability and comfort and user experience and satisfaction ($r = 0.113$, $p = 0.218$) were all nonsignificant. Similarly, data accuracy and reliability showed weak, nonsignificant correlations with impact on training and performance ($r = 0.051$, $p = 0.583$) and user experience and

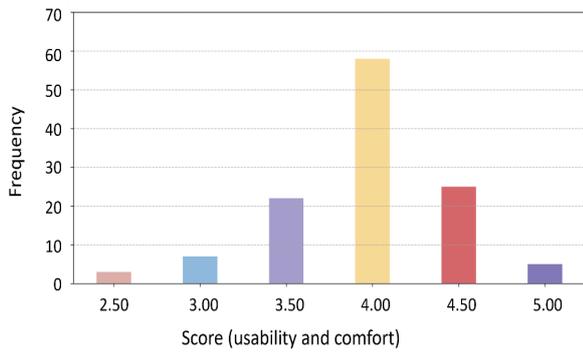


Fig. 5. (Color online) Score and frequency of usability and comfort.

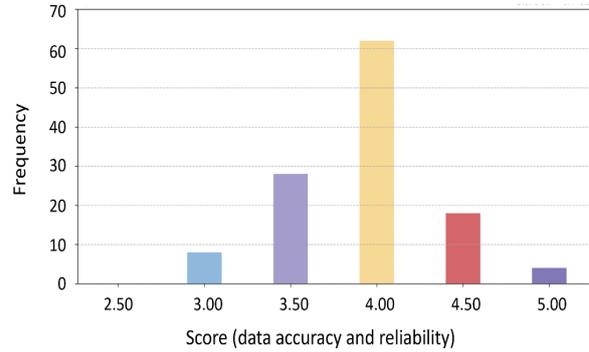


Fig. 6. (Color online) Score and frequency of data accuracy and reliability.

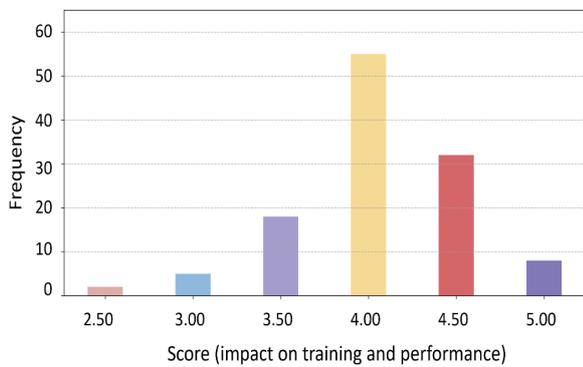


Fig. 7. (Color online) Score and frequency of impact on training and performance.

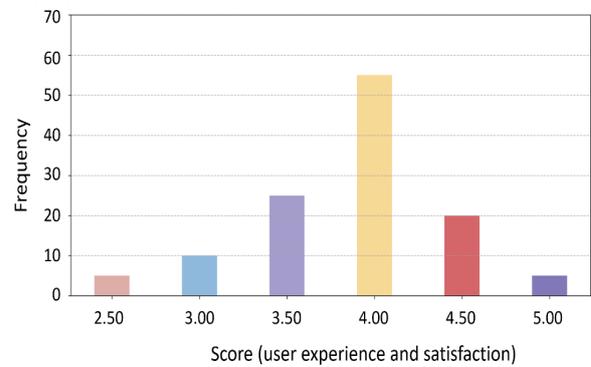


Fig. 8. (Color online) Score and frequency of user experience and satisfaction.

Table 2
Descriptive statistics of questionnaire survey results.

	Number of respondents	Minimum score	Maximum score	Mean score	SD
Usability and comfort	120	3.00	5.00	4.0021	0.46460
Data accuracy and reliability	120	2.75	4.75	4.0458	0.41756
Impact on training and performance	120	2.50	5.00	4.0250	0.51694
User experience and satisfaction	120	2.75	5.00	4.0104	0.45880

Table 3
Correlation analysis results.

Variable	Usability and comfort	Data accuracy and reliability	Impact on training and performance	User experience and satisfaction
Usability and comfort	1	-0.057 (<i>p</i> = 0.534)	-0.064 (<i>p</i> = 0.490)	0.113 (<i>p</i> = 0.218)
Data accuracy and reliability	-0.057 (<i>p</i> = 0.534)	1	0.051 (<i>p</i> = 0.583)	0.121 (<i>p</i> = 0.189)
Impact on training and performance	-0.064 (<i>p</i> = 0.490)	0.051 (<i>p</i> = 0.583)	1	-0.014 (<i>p</i> = 0.876)
User experience and satisfaction	0.113 (<i>p</i> = 0.218)	0.121 (<i>p</i> = 0.189)	-0.014 (<i>p</i> = 0.876)	1

satisfaction ($r = 0.121, p = 0.189$). The correlation between user experience and satisfaction and impact on training and performance was essentially zero ($r = -0.014, p = 0.876$). These results indicate that the variables were not significantly connected, suggesting that participants' perceptions of usability, accuracy, performance impact, and satisfaction were independent. The diversity of wearable devices and differences in user purposes, training methods, and device features contributed to such a lack of significant correlations, as these factors shape individual experiences differently.

Table 4 shows the results of MANOVA, which examined the effects of usability and comfort, and data accuracy and reliability on the dependent variables. In the analysis, impact on training and performance, and user experience and satisfaction were dependent variables in the MANOVA model, not predictors. MANOVA tests the effects of independent variables (usability and comfort, data accuracy and reliability, and their interaction) on multiple dependent variables simultaneously.

In MANOVA, the intercept was highly significant across all multivariate tests ($p < 0.001$), confirming that the model explained variance in the dependent variables. Usability and comfort did not show significant effects (Wilks' Lambda = 0.800, $F = 1.062, p = 0.397$), and data accuracy and reliability approached but did not reach statistical significance (Wilks' Lambda = 0.732, $F = 1.739, p = 0.054$). The interaction between usability and comfort, and data accuracy and reliability was also nonsignificant (Wilks' Lambda = 0.498, $F = 0.968, p = 0.541$). These results indicate that while usability and accuracy are important individual dimensions, their effects were not strong enough to yield statistically significant differences in the multivariate model. Moreover, the lack of significant interaction indicates that combining usability and accuracy did not amplify their effects. Overall, the MANOVA results support the correlation analysis by showing that users' experiences with wearable devices in sports training were not strongly determined by these variables, but rather shaped by diverse contextual and personal factors.

The correlation analysis and MANOVA results show that these variables were not significantly correlated with one another, nor did usability and accuracy exert significant multivariate effects, while the participants rated usability, accuracy, performance impact, and satisfaction highly in descriptive statistics. This implies that athletes' positive perceptions of wearable devices are shaped more by individual contexts and diverse device features than by direct statistical relationships among the measured variables.

5.2 Discussion

The results of this study show that wearable devices are technically robust and widely accepted by athletes. With mean satisfaction scores consistently exceeding 4.0, the results demonstrate a strong consensus of the participants regarding usability, accuracy, and impact on training. These findings align with previous research indicating that user-friendly designs and reliable measurements are primary drivers for the continued adoption of wearable technology.^(1,2) Furthermore, the quantitative improvements observed confirm the transformative role of sensor technology: soccer teams utilizing GPS-embedded vests reported an 8–12% performance gain

Table 4
Results of MANOVA.

Effect	Value	<i>F</i>	Degree of freedom for hypothesis	Degree of freedom for error	Significance (<i>p</i>)
Intercept					
Pillai's Trace	0.99	3489.757	2	72	0
Wilks' Lambda	0.01	3489.757	2	72	0
Hotelling's Trace	96.938	3489.757	2	72	0
Roy's Largest Root	96.938	3489.757	2	72	0
Usability and comfort					
Pillai's Trace	0.208	1.061	16	146	0.398
Wilks' Lambda	0.8	1.062	16	144	0.397
Hotelling's Trace	0.239	1.062	16	142	0.397
Roy's Largest Root	0.182	1.66	8	73	0.123
Data accuracy and reliability					
Pillai's Trace	0.289	1.762	14	146	0.05
Wilks' Lambda	0.732	1.739	14	144	0.054
Hotelling's Trace	0.338	1.716	14	142	0.058
Roy's Largest Root	0.187	1.949	7	73	0.074
Usability × Data accuracy interaction					
Pillai's Trace	0.584	0.971	62	146	0.543
Wilks' Lambda	0.498	0.968	62	144	0.541
Hotelling's Trace	0.684	0.965	62	142	0.539
Roy's Largest Root	0.535	1.26	31	73	0.209

within one year, while swimming programs achieved a 23% reduction in milestone completion time and a 20% decrease in recovery duration. In rugby, biomechanical monitoring effectively reduced injury-related downtime, ensuring higher player availability.

The multivariate analysis revealed no significant correlations among usability, accuracy, performance impact, and satisfaction. This lack of interaction suggests that an athlete's positive perception is not a byproduct of a single statistical relationship but is mainly shaped by user experiences and contextual factors, such as sport type, specific training goals, and device-specific features.⁽³⁾ These results also underscore that for a device to be effective, it must integrate seamlessly into an athlete's daily routine, providing accurate insights without adding friction to the training environment.⁽⁴⁾

The synergy between advanced sensors, such as ECG-based chest straps, IMUs, and photoplethysmography, and ML algorithms creates a holistic ecosystem for personalized training. By analyzing HRV, accelerometer signals, and respiratory metrics, various models provide early warnings for overtraining and injury risk. Furthermore, rapid feedback-driven adjustments allow athletes to regulate their intensity and maintain motivation in real time, a factor Bourdon *et al.* identified as key to adaptive training success.^(3,27)

Despite these advancements, barriers to the widespread adoption of the devices remain, including data privacy and measurement reliability. The sensitivity of health data, combined with inconsistent privacy policies across manufacturers, might cause uncertainty for coaches and athletes. Furthermore, consumer-grade devices often exhibit fluctuations in heart rate and

caloric expenditure during high-intensity sessions when compared with professional-grade equipment, potentially leading to flawed training decisions.⁽¹⁹⁾ User engagement also remains a significant barrier. Many athletes discontinue use within six months due to battery maintenance, discomfort, or data fatigue from overly complex metrics. To maximize the potential of wearable technology, it is necessary to train athletes and coaches to interpret data accurately, transition from tracking everything toward specific, goal-oriented metrics, and encourage collaboration between technology developers and sports organizations to enhance the user experience while ensuring rigorous data security.

6. Conclusion

The transformative impact of wearable devices in modern sports training was verified in this study, demonstrating their ability to provide real-time, dynamic, and personalized feedback. The participants in this study reported high satisfaction across usability, accuracy, comfort, and performance impact, with mean scores exceeding 4.0. Performance gains of 8–12% in soccer, a 23% reduction in milestone achievement time in swimming, and reduced injury downtime in rugby also underscore the tangible benefits of sensor-driven training.

By examining the relationship between advanced sensor development and athlete outcomes, technologies such as photoplethysmography, ECG, accelerometers, and GPS modules are validated for precise biometric monitoring, whereas ML algorithms and mobile applications transform raw data into actionable insights. Such advancements foster adaptive training programs, proactive injury prevention, and enhanced tactical decision-making.

As wearable devices continue to evolve, their role is expected to expand beyond performance optimization to holistic athlete well-being. Advancements in flexible, skin-integrated sensors, smart textiles, energy harvesting, and wireless charging enable continuous monitoring and prolonged data collection. Integration with medical systems, augmented and virtual reality platforms, and secure data-sharing protocols, including blockchain, further strengthens trust, accuracy, and adoption. Advanced predictive analytics powered by ML and AI can refine injury detection, performance forecasting, and individualized training strategies.

Despite such advantages, challenges remain in data privacy, measurement accuracy, and sustained user engagement. Addressing these issues requires collaboration among technology developers, sports scientists, healthcare professionals, and athletes. By prioritizing robust data security, continuous sensor precision, and effective education on data utilization, wearable devices can reach their full potential. Wearable devices are not merely tracking tools but powerful enablers of precise coaching, athlete empowerment, and long-term well-being. As sensor technology matures, these devices contribute significantly to athletic success, injury prevention, and inclusivity, solidifying their role as a cornerstone of modern sports science.

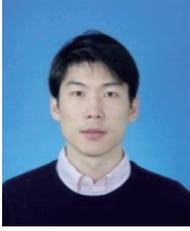
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