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Real-time Sensor Monitoring System for University Sports Training

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Advancements in material sciences and sensor technology have transformed sports engineering, enabling the real-time monitoring of physiological, biomechanical, and environmental parameters in university athletics. We reviewed recent developments and implications of real-time sensor monitoring systems in university sports training, emphasizing their effectiveness, challenges, and contributions to sensor technology development. The data collected from 2019–2024 publications across PubMed, the Institute of Electrical and Electronics Engineers Xplore, Web of Science, and SPORTDiscus focused on athletes aged 18–25. The results showed that real-time monitoring systems improved training efficiency by 18–35%, reduced overtraining incidence by 28%, and enhanced skill acquisition rate, by up to 35% compared with traditional methods. Integrated multisensor platforms combining inertial measurement units, GPS, and environmental sensors are 40–60% more effective in enhancing performance and preventing injuries than single-sensor systems. Case studies from universities such as Notre Dame, Stanford, and Vermont in the United States of America demonstrated the successful implementation of the real-time monitoring system. The results provide a basis for next-generation sensor and material development, including MXene-based elastomer substrates and triboelectric nanogenerators, supporting the development of adaptive, high-durability, and energy-autonomous sensor architectures for high-stress collegiate training environments.

1. Introduction

Advancements in material sciences and MEMSs have reshaped sports engineering. Modern sports training systems increasingly rely on active transduction materials and sensor technologies that enable real-time quantification without restricting athletic movement. Piezoresistive polymer composites, flexible indium gallium zinc oxide semiconductors, and advanced optical photoplethysmography (PPG) arrays are now employed to continuously capture physiological states.[1,2] For example, the transition from conventional rigid electrodes to elastic, carbon-nanotube-embedded conductive fabrics has minimized contact impedance and skin

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irritation under high-sweat conditions, allowing reliable real-time electrocardiogram (ECG) data acquisition during high-intensity training thresholds.[3] By analyzing engineering constraints, such as hysteresis in stretchable strain sensors and signal-to-noise ratios in optical paths, coaches and sports engineers can optimize data-driven athletic loads.

Whereas real-time sensor monitoring platforms provide universal benefits across all stages of athletic development, collegiate or university-level training environments have attracted scientific and architectural research interests. University athletics represents a critical transitional phase where athletes subject their fully matured or near-maturity musculoskeletal systems to near-elite training volumes, higher mechanical velocities, and extreme physiological stress. Capturing these high-intensity dynamics requires high-fidelity multisensor networks characterized by rapid sampling rates [>500 Hz for inertial measurement units (IMUs)], complex data-fusion algorithms that combine biomechanical and physiological streams, and robust wireless mesh networks capable of handling dense data throughput without latency. In contrast, sports training for high school students presents different physiological and mechanical constraints.[4] Adolescents undergo rapid, uneven skeletal elongation and asynchronous muscular development, which alter centers of mass and joints of arms over short periods. This anthropometric volatility makes them highly susceptible to growth-plate injuries, such as epiphyseal slips, and overuse syndromes if training loads are poorly managed. Highly sensitive flexible strain gauges and pressure-sensing insoles are used to monitor changing gait symmetries and localized joint loading anomalies caused by growth spurts.[5] However, because university programs possess centralized infrastructure, technical funding, and processing power to manage full-scale, multimodal sensor telemetry in real time, they serve as the primary deployment model for advanced architectures before adaptation to adolescent injury-prevention applications.

In higher education, athletic programs foster physical wellness, psychological well-being, and personality development beyond competition, collectively contributing to students' growth.[6] University sports training programs are aimed at enhancing training effectiveness and athlete safety while simultaneously supporting academic achievement.[7] Conventional training methods, though widely adopted, often lack immediate feedback and personalized intervention, leading to risks such as overtraining and injury. The integration of advanced monitoring technologies has enabled a precise understanding of performance, physiological responses, and adaptations to training loads (Fig. 1).[8] These technologies have transformed subjective analysis into objective, data-driven, and personalized methodologies increasingly integrated with physiology and predictive health analytics to enhance performance and reduce injury risks.

Modern university sports training programs have become sophisticated by incorporating AI, machine learning, and IoT into comprehensive monitoring systems. Such programs assist coaches and sports scientists in making informed decisions based on objective sensor data rather than observation alone. Multisensor systems are used to monitor biomechanical parameters, physiological markers, and environmental conditions simultaneously, enabling personalized training programs that enhance athletic performance and reduce injury risks.[9,10] Engineering advances in sensor materials and MEMS technologies, such as flexible substrates, stretchable conductors, and low-power wireless modules, are vital to ensuring accuracy, durability, and unobtrusiveness in dynamic training environments.[11,12]

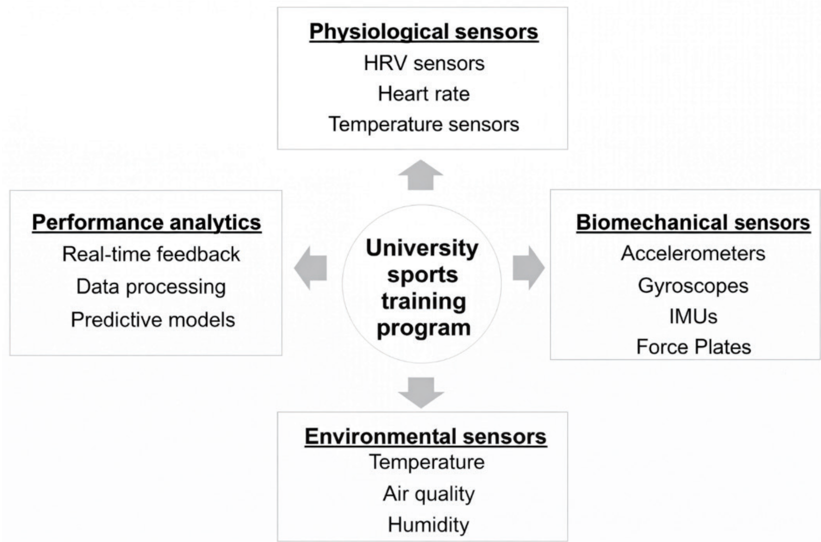

Fig. 1. Integration of sensors in university sports training (HRV: heart rate variability; IMUs: inertial measurement units).

In this study, we examined the current state of sensor monitoring technologies adopted in university sports training. Rather than presenting an experimental study, we reviewed the existing literature to highlight the effectiveness, challenges, and potential of these systems in improving training outcomes.[13] Specifically, we evaluate the impact of sensor technology on enhancing training effectiveness and injury prevention, identify best practices for successful implementation, and analyze engineering constraints that affect deployment. The effects of real-time sensor data on injury prevention and performance enhancement, as well as barriers hindering adoption in university sports, are also discussed.

2. Background Knowledge

2. Literature review

Sensor technology integration in sports training has been extensively researched, particularly concerning real-time monitoring. Seshadri *et al.* assessed the reliability of wearable sensors for measuring internal (e.g., heart rate) and external (e.g., acceleration) physiological loads of athletes,[1] as accurate measurement is crucial for optimizing athlete performance and minimizing injury risk. The study results indicated that sensor technology, when combined with physiological and health analytics, provided important information on athletic environments to enhance training effectiveness and safety.[1] Recent research results showed that the integration of sensor systems with AI and machine learning facilitates real-time data processing and autonomous decision-making for effective sports training.[2] Tang *et al.* employed deep reinforcement learning with sensor data from track and field athletes to improve the accuracy of movement pattern recognition and provide immediate feedback for correction (Fig. 2).[9]

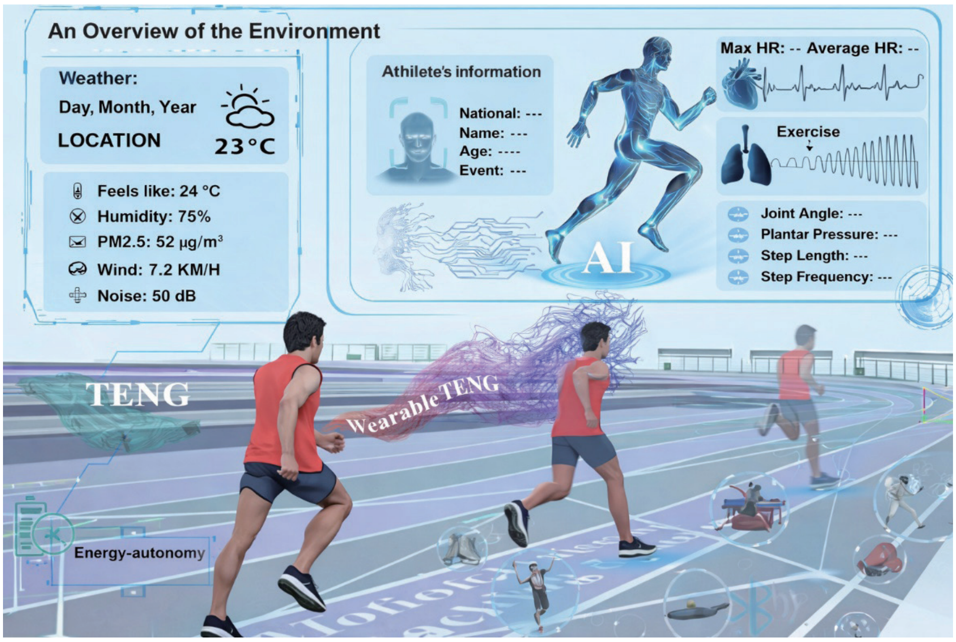

Fig. 2. (Color online) Triboelectric nanogenerator (TENG)-boosted smart sports with energy autonomy and digital intelligence.[10]

The literature review results in this study showed that AI-based strategies are transforming athlete monitoring from single-parameter monitoring to predictive modelling using multiple parameters to forecast injury risk or performance, enabling proactive intervention. Concurrently, multiple sensors are integrated into a unified platform that combines data from heart rate monitors, IMUs, GPS, and environmental sensors and presents an athlete's physiological status (Fig. 3).[14] Such detailed monitoring allows for a sophisticated interpretation of training responses that takes into consideration physiological and biomechanical parameters and contextual factors. It also enables the formulation of training optimization strategies that are adjusted in accordance with an athlete's changing condition to yield effective and safe outcomes. A transition from traditional subjective monitoring to continuous, automated, and integrated monitoring systems for athletes was identified in the literature review.

To evaluate the architectural advantages of such automated systems, they must be compared with traditional systems. Traditional methods adopt retrospective, subjective, and episodic tracking protocols that rely on manual entry and human observation. The traditional methods require paper-based logs or digital spreadsheets where athletes self-report their perceived exertion, the visual observation of a technique by a coach from the sidelines, and a delayed post-session video playback analysis. Although simple, the traditional method suffers from significant recall bias, capturing data only after training cycles have completed, and lacks intrasession physiological telemetry (such as real-time multilead ECG readings or instantaneous joint angle tracking). Consequently, traditional mechanisms cannot provide immediate corrective biological or biomechanical feedback loops and fail to detect structural load accumulation or micro-kinematic asymmetries until an acute injury or severe systemic overtraining has already occurred.[15]

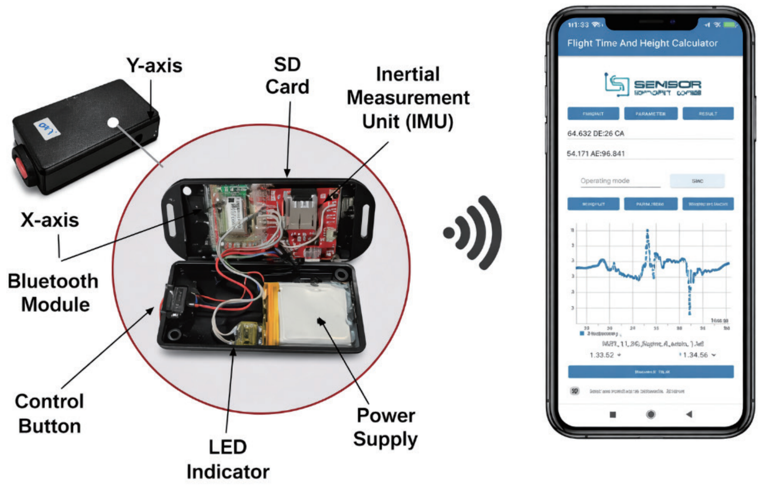

Fig. 3. (Color online) (a) Developed system and (b) customized smartphone application for measurement of flight time and reached height of athletes.[14]

Fused data from diverse sensors are required to provide information on an athlete's status.[14] Such detailed monitoring enables a more sophisticated approach to interpreting training responses, taking into account physiological and biomechanical parameters, as well as contextual factors collectively. This has led to the fact that training optimization strategies can be made dynamic to keep up with the dynamically changing athlete condition, thereby becoming more effective and safe.

2.2 Sensors in sports training

Wearable sensors are widely used in sports training owing to their ability to collect physiological and physical data. Heart rate variability (HRV) is the most popular parameter to monitor as a key indicator of autonomic nervous system activity and recovery status.[14] Polar H10, manufactured by Polar Electro Oy, is one of the most accurate and reliable heart rate sensors used for athletes and fitness enthusiasts. It incorporates an ECG to ensure precise readings even during intense exercise. Devices such as Polar H10 are increasingly integrated into athletic clothes or wristbands, balancing comfort with scientific rigor.

Wearable sensors are widely used in sports training because of their ability to collect physiological and physical data through targeted physical transduction. HRV monitoring relies on optical PPG or chest-strap ECG sensors. For example, high-fidelity systems incorporate multi-wavelength optical sensor modules comprising Ga–As infrared-emitting diodes paired with silicon photodiodes to achieve accurate volumetric blood flow registration through the dermis, compensating for motion artifacts via integrated adaptive filtering algorithms.[16] Simultaneously, biomechanical analysis has advanced through micromachined IMUs. Modern sports IMUs integrate triaxial capacitive MEMS accelerometers, vibrating-structure polysilicon gyroscopes, and anisotropic magnetoresistive magnetometers on a single CMOS die.[17] These devices utilize high sampling frequencies exceeding 500 Hz to map high-velocity joint kinematics without signal clipping. The raw sensor output, measured as differential capacitance or voltage changes proportional to applied Coriolis forces or acceleration, is processed using onboard Kalman filters to deliver highly precise 3D spatial orientation matrices.

Sensors and accelerometers have been significantly advanced and are mainly used for biomechanical analyses. IMUs, equipped with triaxial accelerometers, gyroscopes, and magnetometers, are used to track fine-grained movements of limbs and the entire body in three dimensions (Fig. 4).[18] Their high sampling frequencies, exceeding 500 Hz, ensure the reliable monitoring of rapid movements. These sensors measure acceleration, angular velocity, and orientation, which are crucial for evaluating athletic skills and quantifying workload.

Environmental sensors are essential components of wearable devices. Temperature and humidity sensors collect data related to thermoregulation and exertion levels. Monitoring such environmental parameters leads to the adjustment of training loads to prevent heat-related illnesses or suboptimal performance. Additional environmental parameters, such as air quality indices and ultraviolet radiation levels, are also monitored to ensure a safe outdoor training environment.

Positioning technologies and GPS enable the spatial and tactical analysis of sports activities. Current systems precisely track displacement, velocity, and acceleration.[11] This information is critical in field sports (e.g., soccer and rugby), where understanding movement patterns, tactical execution, and energy expenditure management is paramount. The integration of GPS with other sensors facilitates comprehensive training monitoring, bridging the gap between physiological measurements and tactical performance.

2.3 Real-time sensor data

Real-time athletic data are useful for sports training and performance enhancement. They enable immediate feedback to athletes and coaches and real-time adjustments to training intensity, mechanics, or strategy. This contrasts with traditional postsession analysis methods,

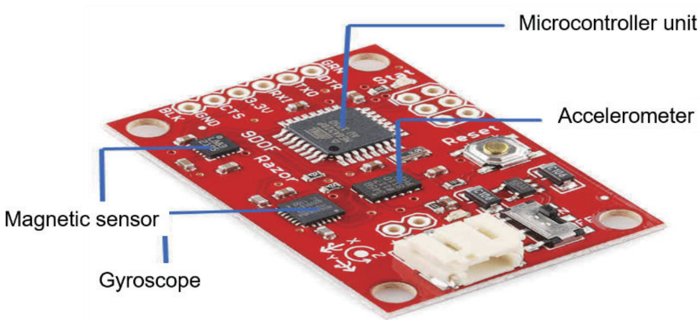

Fig. 4. (Color online) Sensors used in IMU.[10]

which cannot provide immediate corrective intervention. Training incorporating real-time feedback enhances skill acquisition, reduces technical errors, and optimizes training efficiency.[12] It also contributes to injury prevention. Consistent biometric and biomechanical monitoring facilitates early intervention through the early identification of fatigue, asymmetry, or movement deviations that often precede an injury.[13] Timely alerts based on real-time sensor data prompt athletes to reduce training load or modify their skills to prevent injuries caused by the overuse of muscles, which is common in sports.

Recovery monitoring is indispensable in training management. HRV, sleep quality, and survey data are used to assess recovery status and provide personalized recovery programs.[14] The parameters obtained in real time also enable the dynamic adjustment of training loads and an optimal balance between stress and rest. Methods using the parameters enhance performance while mitigating injury or burnout risks. Personalized recovery protocols based on real-time data also increase training responsiveness and long-term athlete durability.

Advanced data analytics in real time enable the data-driven assessment of training effectiveness and athlete development. By correlating training inputs with performance outcomes and identifying hidden patterns, effective training programs can be developed for long-term planning, performance optimization, and recovery monitoring. Table 1 presents sleep quality and recovery metrics before the overload period (T1), after the overload period (T2), and after the recovery period (T3). The results represent 7-day average values on the test days.[14]

Despite notable advancements, the application of previous research results to university sports is still limited as the results focus on high-performance sports, which benefit from substantial resources, specialized services, and strictly regulated conditions. As university athletic programs are limited in budget and developed for diverse athletes with different fitness levels and technical proficiencies, differentiated approaches based on real-time sensor data are necessary.

2.4 Transduction materials and processing architecture

To deploy multisensor platforms in volatile collegiate training environments, the selection of appropriate underlying sensor encapsulation and active materials is essential. Biomechanical flexible strain sensors frequently leverage polydimethylsiloxane substrates doped with silver nanowires or MXene flakes to capitalize on their high gauge factors and rapid electromechanical recovery times under repetitive loading cycles.[19] MXenes are 2D inorganic compounds consisting of transition metal carbides, nitrides, or carbonitrides. They are similar to graphene but are made from titanium, vanadium, or molybdenum, and their surfaces are covered with hydrophilic functional groups. In sports engineering and athletic training, MXene flakes are integrated into flexible, skin-tight polymers, such as silicones or rubbers, to create advanced wearable strain and motion sensors. They are used to enhance sports training through high-precision joint tracking, showing rapid response, low hysteresis, and sweat-resistant biocompatibility.[20]

Recent advancements in energy-autonomous sensor networks have introduced TENGs into athletic footwear and apparel. These self-powered sensors employ microstructured

Table 1
Sleep quality and recovery metrics determined using real-time monitoring data.[14]

Parameter score	T1	T2	T3	T1–T2 (range)	T2–T3 (range)	T1–T3 (range)
Athlete sleep screening questionnaire (1–5)	4.9 ± 2.1	4.5 ± 1.8	4.8 ± 2.3	−0.29 (−0.70–0.12)	0.15 (−0.26–0.55)	−0.06 (−0.46–0.34)
Subjective sleep quality (1–5)	3.3 ± 0.4	3.2 ± 0.5	3.4 ± 0.5	−0.16 (−0.56–0.24)	0.44 (0.02–0.86)	0.16 (−0.24–0.57)
Sleep continuity (1–5)	3.2 ± 0.6	3.1 ± 0.6	3.0 ± 0.7	−0.18 (−0.58–0.23)	−0.29 (−0.69–0.12)	−0.52 (−0.94–−0.08)
Sleep score (0–100)	75.9 ± 7.4	75.6 ± 7.8	75.2 ± 9.0	−0.08 (−0.48–0.32)	−0.08 (−0.48–0.32)	−0.15 (−0.55–0.25)
Sleep time (h)	7.2 ± 0.8	7.1 ± 0.8	7.2 ± 0.2	−0.20 (−0.60–0.20)	0.21 (−0.20–0.61)	0.00 (−0.40–0.40)
Actual sleep (%)	93.7 ± 1.6	93.6 ± 1.9	93.1 ± 3.5	−0.06 (−0.46–0.34)	−0.25 (−0.65–0.16)	−0.26 (−0.66–0.15)
Heart rate (beats per minute, bpm)	51.4 ± 6.9	51.7 ± 7.7	50.8 ± 8.6	0.10 (−0.31–0.51)	−0.24 (−0.65–0.18)	−0.16 (−0.57–0.25)
Root mean square of successive differences (ms)	70 ± 22	71 ± 24	71 ± 23	0.10 (−0.31–0.51)	−0.01 (−0.42–0.40)	0.10 (−0.32–0.50)
Breathing rate (bpm)	13.7 ± 1.0	13.7 ± 0.9	13.7 ± 0.9	−0.26 (−0.67–0.16)	0.00 (−0.41–0.41)	−0.28 (−0.69–0.14)

polytetrafluoroethylene or fluorinated ethylene propylene films in contact–separation modes with nylon layers to convert kinetic mechanical impacts directly into electrical signal pulses.[21] The resulting voltage peaks serve a dual purpose as highly sensitive, unpowered force-sensing resistors quantifying ground reaction forces during sprinting or jumping, while simultaneously charging micro-supercapacitors within the wearable sensor node network.

3. Methodology

We collected sensor data for real-time monitoring in university sports training from articles published in sports science, engineering, computer science, and education. The following databases were searched: PubMed for biomedical research, the Institute of Electrical and Electronics Engineers Xplore/Web of Science for technological advancements, and SPORTDiscus for sport-related studies and training. Additionally, we searched articles on Google Scholar and professional organization portals to find relevant conference proceedings papers, technical reports, and case study reports. The selection criteria for articles were as follows: athlete's age of 18–25 years old, publication years between 2019 and 2024, and topics related to real-time monitoring, wearable sensors, sensor technologies, sports training, university athletes, training effectiveness, injury prevention, and observation. Articles on professional athletes were included only if their results were directly applicable and transferable to university sports, while articles with research results of athletes under 18 years old and rehabilitation were excluded to maintain the specificity of the keywords. Only articles written in English were selected in the analysis.

The collected articles were analyzed using a narrative and thematic method. Data for further analysis were extracted to explore relationships, discrepancies, and gaps in university sports training. There might be biases because of the differences in data sources and contexts of selected articles. Given the rapid evolution of sensor technologies, the selected articles may not fully present the recent advancements. The scarcity of longitudinal studies also constrains the understanding of the continuous effects of sensor data. Despite these limitations, an integrated dataset and its analysis results provide a reference for researchers, practitioners, and decision-makers to enhance university sports training programs.

4. Results

4.1 Effect of sensor technology

Previous research results underscore the transformative effect of wearable sensor technologies on university sports training, presenting significant advancements in training and intervention personalization. Shaheen *et al.* utilized IMUs and electromyography sensors to determine the heart rate and muscle activation of athletes during training.[22] Enhanced heart rate control (a mean decrease of 4.3 bpm, $p < 0.01$) and muscle activation patterns indicated improved neuromuscular control owing to sensor integration. Real-time monitoring results showed that biometric and motion sensor data contributed to the reduction of injury risk through early fatigue detection and workload adjustments, and improved subjective well-being scores.[23]

We identified groups of sensor technologies for various monitoring tasks in sports training. Physiological sensors were employed in most monitoring systems, with heart rate monitoring being the most widely adopted owing to its reliability, cost-effectiveness, and validity in determining training loads. Heart rate monitoring technologies with advanced sensors enable HRV measurements with which the autonomic nervous system function and recovery were assessed.[24] Advanced systems incorporate core temperature, hydration status, and respiratory rate as physiological parameters for comprehensive physiology monitoring (Fig. 5).

The rapid advancement of biomechanical sensors, including accelerometers and gyroscopes, ensures detailed movement analyses. These sensors are used to monitor body movement, quantify training loads, and record subtle changes in skills. The integration of multiple sensors in IMUs leads to accurate real-time movement analysis, providing personalized feedback on faults in skills or compensatory body movements that could lead to injuries. These sensors are increasingly integrated into existing equipment or even clothes, which enhances user acceptance and data quality by minimizing interference caused by natural body movement.

Environmental monitoring sensors provide crucial information on responses to training programs and safety. Temperature, humidity, and air quality sensors help prevent heat-related illnesses and respiratory complications, contributing to optimal training conditions. Positioning technologies such as GPS enable the analysis of movement patterns, tactical decisions, and training load distribution across different training venues.[26] The integration of positional and environmental data enhances the interpretation of sensor data and the understanding of physiological and biomechanical parameters. Sensor technologies are categorized as shown in Table 2.

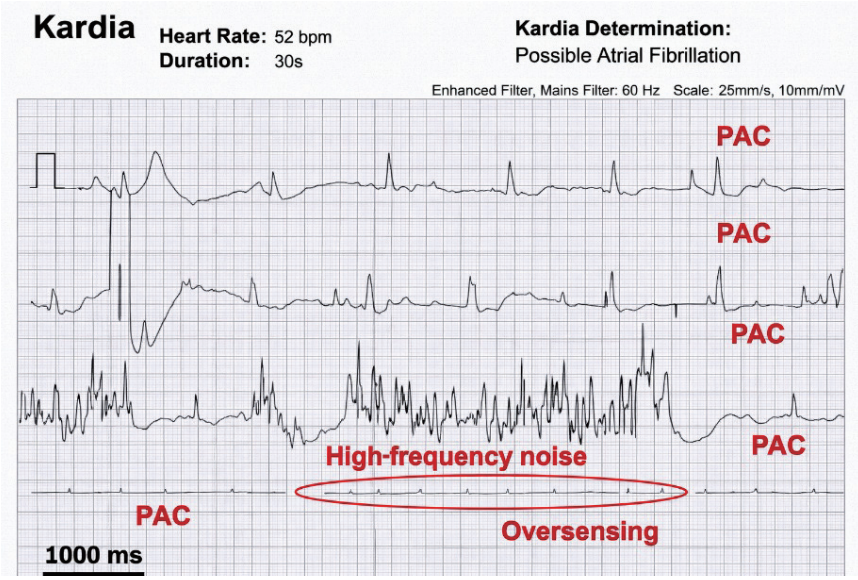

Fig. 5. (Color online) ECG recording of heart activity with AliveCor Kardia. High-frequency noise indicates an incorrect determination of atrial fibrillation with frequent premature atrial contractions (PACs), a benign cardiac rhythm abnormality.[25]

Table 2
Categorization of sensor technologies.

Category	Purpose	Implementation complexity	Injury prevention	Data quality	Adoption rate	Benefit
Physiological sensor	Heart rate monitoring	Low	Medium	High	90%	Real-time intensity monitoring, HRV analysis
	Core temperature	Medium	High	High	35%	Heat illness prevention
	Hydration	High	Medium	Medium	15%	Dehydration prevention
Biomechanical sensor	Integration in IMU	High	High	High	60%	Movement analysis, skills optimization
	Integration in platforms	Very high	High	Very High	25%	Precise load measurement
	Wearable devices	Medium	High	High	70%	Activity tracking, load monitoring
Environmental sensor	Positioning tracking	Low	Low	High	85%	Position analysis, distance tracking
	Weather monitoring	Medium	High	High	45%	Environmental safety
Integrated sensor	Multisensor platforms	Very high	Very high	Very high	20%	Comprehensive monitoring

4.2 Effectiveness of real-time monitoring

Systems providing immediate feedback in training are more effective than those relying on postexercise analysis.[27] The timely feedback allows athletes and coaches to make instantaneous adjustments to training intensity, mechanics, or strategy, leading to efficient and effective training. Such immediate feedback loops enhance training effectiveness, measured using technical skill acquisition acceleration and rapid adaptation to aerobic thresholds, by 20–35% compared with traditional training programs relying on postsession video or manual logs. This performance can be achieved by adjusting real-time kinetics to minimize the consolidation of incorrect muscle memory path-mechanics during repetitive athletic cycles.(28)

However, the applicability of real-time monitoring sensors in sports training varies significantly depending on implementation policies and existing training programs. Furthermore, integrating diverse sensors into a single system must be optimized to monitor multiple parameters at the same time. Multiple sensor integration enables the monitoring of physiological responses, movement quality, and environmental factors to enhance performance and prevent injuries. To monitor an athlete's physiological status, data must be collected from multiple sensors. The cumulative data packet payload sizes and active computational power consumption patterns of multisensor fusion arrays are 40–60% larger than those of standalone, single-sensor-based monitoring. Managing this increased payload requires more robust on-chip digital signal processors to simultaneously process high-frequency serial peripheral interface (SPI) and inter-integrated circuit (I2C) sensors, with constraints on the design of the wearable battery management circuitry.

Several universities have successfully implemented real-time monitoring systems across various sports programs. The University of Notre Dame in the United States of America (USA) has deployed integrated monitoring systems in its athletic programs, presenting the feasibility of large-scale sensor technology adoption.(29) The system combines heart rate monitoring, GPS tracking, and biomechanical analytics into a unified platform for athlete monitoring and intervention in football, basketball, soccer, and track and field. Stanford University's (USA) swimming programs exemplify the effectiveness of a skill-specific sensor monitoring system.(30) By incorporating underwater motion sensors, such as high-speed accelerometry for track racing, their system provides real-time biomechanical feedback. The feedback has enabled the enhancement of skill acquisition rates by 35% compared with their traditional training methods. The system's capacity for the instant analysis of stroke mechanics and running gait feedback enhances athletes' skills and performance.

A smaller-scale, yet effective, implementation was observed at the University of Vermont (USA). In their program, HRV and biomechanical parameters are used to optimize training programs. The program has increased the training efficiency by 18% and decreased overtraining incidence by 28% in cross-country and cycling. This case highlights substantial benefits with minimal investment in sensor technology. The United States Military Academy's athletic monitoring program is applied in multiple disciplines. Their system integrates physiological monitoring, environmental sensors, and athletic performance analysis, catering to athletes and military fitness requirements. The program has improved overall fitness and reduced the training-related medical injury of cadets. This underscores the potential of sensor monitoring to contribute to broader health maintenance in a university.

The University of Bath in the United Kingdom implemented a multimodal monitoring system designed for elite student athletes to balance competitive sports conditioning with higher education academic schedules. This specialized integration was implemented to mitigate the dual-career conflict by establishing a continuous data-driven loop between physiological strain and cognitive workloads.(15) Their system calculates each athlete's acute-to-chronic workload ratio (ACWR) by cross-referencing external training loads, derived from high-frequency GPS displacement and triaxial IMU accelerometry, with internal physiological metrics that are captured by using wireless nocturnal HRV bands and microfluidic sweat lactate patches. When academic stress peaks, such as during mid-term or final examination periods, the system registers the resulting elevated baseline resting heart rates and depressed root mean square of successive differences. ACWR thresholds exceeding safe boundaries (>1.5) indicate a high risk of overtraining or stress-induced injury. In such cases, the system automatically feeds prescriptive, real-time workload-reduction recommendations directly to the coaching staff dashboard. This helps adjust training levels to preserve the athlete's neurological recovery and sleep continuity without compromising long-term athletic adaptation.

5. Discussion

5.1 Advantages and challenges

A complex landscape was observed for the successful integration of real-time monitoring sensors in university sports training. Performance enhancement and injury prevention observed in various studies strongly support the capability of sensor technology, which improves university sports programs (Fig. 6). However, the benefits depend on the quality of

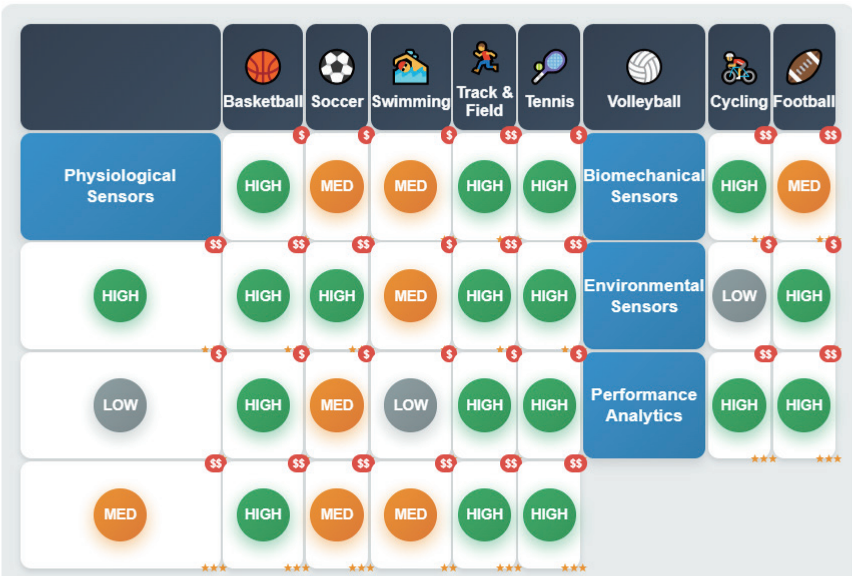

Fig. 6. (Color online) Sensor application matrix in University of Bath's monitoring system.

implementation, institutional support, and seamless integration with existing training programs and equipment. Real-time sensor monitoring systems outperform single-sensor systems in university program design and resource optimization. The benefits outweigh the initial high costs of implementing the real-time sensor monitoring system. Therefore, a multifaceted approach is required for the successful introduction of the system.

The multisensor system enhances skill acquisition and development through real-time feedback and reduces the time and specialized expertise requirements. The system provides objective and consistent feedback and compensates for resource limitations by enhancing training quality.(31) This highlights the benefit of sensor monitoring technology in optimizing training programs of universities with resource constraints. The system also ensures injury prevention. The continuous longitudinal profiling of kinetic asymmetries has demonstrated a 25% reduction in lower-extremity overuse injury rate among athletes.(32,33) This mitigation leads to the enhancement of athlete well-being since predictive machine learning algorithms can identify microstructural drift and structural loading imbalances, such as uneven landing impact forces, before acute ligamentous or bone stress failure manifests.

However, the real-time sensor monitoring system necessitates corresponding training program development with the appropriate assignment of roles and responsibilities, institutional resource allocation, and the adoption of proprietary technology. Effective training programs require a well-defined management system for staff training, process redesign, and continuous technical support. The successful system implementations demonstrate an institutional commitment to the acquisition of the multisensor system. However, appropriate data interpretation processes must be developed for effective training with a new system to provide effective personalized intervention and feedback. Such requirements for data analysis and interpretation capability necessitate substantial investment and appropriate guidelines; as an increased volume of training data is generated, robust solutions for storage, analysis, and longitudinal tracking are demanded.

It is also necessary to balance data-driven decision-making with traditional coaching in training programs to avoid prioritizing sensor-derived feedback and to seamlessly integrate the multisensor system into the existing coaching methodologies. The education and engagement of student athletes are fundamental, along with effective technological implementation. Universities must educate users, such as athletes, coaches, management teams, and technicians, regarding data collection, interpretation, and analysis. Appropriate resource and budg*et all*ocation are necessary for long-term operation, technical support, and staff development.

Universities must establish budget models, taking system establishment, equipment maintenance, software licensing, subscriptions, technical support, and staff training into consideration. The most frequently cited challenge in the adoption of sensor monitoring systems in university sports training programs was the cost. This necessitates sustainable financial planning. For positive outcomes and a sound athlete–coach relationship, self-regulated training programs with the multisensor system need to be established to foster autonomy.

Technical expertise is also required for the effective implementation of sensor monitoring systems, as the system operation and data analytics require experienced and well-trained staff.(34) Universities can hire a new workforce, train their employees, or collaborate with external institutions for continuous technical support. Data management and interpretation pose a complex issue, as sensor systems generate vast amounts of data that require efficient management, analysis, and conversion. Most existing university sports programs lack experts with analytical capability, which diminishes the return on investment in real-time sensor monitoring systems. Therefore, it is necessary to develop robust data management protocols and analytical capacity before system implementation. In dealing with the collected data, data privacy and security are critical concerns, as the data include personal information on physiology, performance, and personal behavior. Universities must establish regulations and guidelines to ensure data security and to use the data ethically. Such a data usage policy is important as student rights and academic policies are critical in universities.

Cultural and practical issues exist in integrating a real-time sensor monitoring system with existing training programs and coaching methodologies, which can be underestimated during implementation planning. Coaching staff might resist adopting a new system or lack confidence in understanding and utilizing the collected data. Therefore, for the successful implementation of the system, detailed management strategies must be formulated to address technical and cultural difficulties in integrating a sensor monitoring system.

5.2 Implementation of advanced system

Since wearable sensor technologies and active materials evolve rapidly, university athletic programs face the recurring risk of technology obsolescence. To mitigate the implementation and upgrading costs, sports monitoring systems must adopt a decoupled, modular system architecture.[35] Such an adoption is enabled by decoupling the sensing elements from the core processing unit. By establishing standardized I2C or SPI buses on flexible printed circuit boards, sensor components can be upgraded without replacing the underlying microcontroller units, power management integrated circuits, or wireless transmitters. System longevity can be ensured without compounding capital costs by leveraging edge computing paradigms and over-the-air firmware deployment.[36]

Instead of purchasing new physical nodes to capture refined biometric parameters, existing sensors can be upgraded remotely using firmware updates. These patches are deployed by advanced embedded digital signal processing algorithms, such as adaptive wavelet transforms or lightweight neural network classifiers. Open-source, nonproprietary wireless communication protocol stack standards, such as Bluetooth Low Energy and message queuing telemetry transport, can be adopted to eliminate vendor lock-in. This interoperability will ensure that next-generation hardware nodes from diverse manufacturers can be seamlessly integrated into the university's cloud architecture, offering an economically sustainable, highly scalable training ecosystem.

5.3 Advancement in sensors and materials

The deployment data and operational limits discussed in this study can be used as a reference for the design of next-generation physical sensors and advanced materials. In sports training, wearable devices are subjected to mechanical stress, rapid multidirectional accelerations, and corrosive biochemical conditions, which must be resolved through advanced sensor technology and material engineering.

Fast joint movements, such as sprinting and throwing, often cause flexible strain sensors to have lowered accuracy owing to viscoelastic relaxation and microcracking. In this study, a need for elastomer substrates reinforced with organized conductive networks is identified, which can be addressed by using carbon nanotubes or cross-linked MXene-polyurethane structures.(37) These materials enable quick recovery and maintain linear resistance changes even during explosive 3D movements. Strong shear forces can cause sensors to peel off or produce motion artifacts. To address this, biocompatible hydrogel-elastomer hybrids have been developed.(38) These show high stretchability (>800%), self-repair ability, and strong adhesion to wet skin, ensuring stable signals even under intense physical activity. Heavy sweating and high salt levels observed in training corrode metal contacts and degrade optical paths in PPG sensors. To address this problem, coatings made from fluorinated silica nanoparticles or laser-etched superhydrophobic polymers are used.(39) The coatings repel moisture and metabolic waste, protecting sensor circuits while keeping devices thin and lightweight.

By defining the operational thresholds, the results of this study provide a basis for identifying performance targets and creating adaptive, durable sensor substrates designed for demanding, high-stress athletic environments.

5.4 Recommendations

To fill the gap observed in the previous research results, longitudinal validity studies on the effectiveness of real-time sensor monitoring systems are required. The majority of previous studies were conducted in a limited period, necessitating further research to verify the long-term benefits of a university’s integration of a real-time sensor monitoring system. Therefore, it is necessary to conduct long-term research to understand how real-time sensor monitoring systems maintain effectiveness and identify the necessary capabilities for sustainable application. Cost-effectiveness also needs to be validated through the evaluation of potential savings in injury prevention, performance gains, and educational value added compared with the initial investment. Diverse resources and environments, encompassing large research institutions and smaller liberal arts colleges, must be evaluated for optimal system configurations and implementation, and the practical valuation of the implementation of a multisensor monitoring program. Through technological assessment, the most effective sensor combinations must be identified for universities of diverse sports and budget levels, enabling them to reasonably budget to maximize the return on investment.

A real-time sensor monitoring system must be integrated into an existing academic system of universities in underdeveloped areas. In such universities, real-time sensor monitoring systems can be integrated with academic systems to provide an integrated education for athletic and academic performance improvement. Additionally, developing autonomy and self-regulation with the help of the system is also needed to demonstrate its long-term value.

The results of this study can be used to offer several options for universities to implement a real-time sensor monitoring system. Feasibility and cost-effectiveness studies are mandatory to integrate advanced sensors, data analytics, and AI models in the system.

6. Conclusions

The review results of real-time sensor monitoring systems in university sports training present a rapidly evolving landscape with substantial promise for both athletic performance and sensor engineering. Significant advancements have been achieved through the integration of AI, machine learning, and IoT, which collectively enable personalized, adaptive training environments. The efficiency of these systems has been validated: real-time feedback improved training effectiveness by 20–35%, while multisensor integration enhanced performance and injury prevention outcomes by 40–60% compared with traditional, delayed-feedback methods. Case study results across universities show measurable benefits, including a 35% increase in skill acquisition, an 18% improvement in training efficiency, and a 28% reduction in overtraining incidence, underscoring the transformative potential of these technologies.

Despite these successes, the widespread adoption of real-time sensor monitoring systems also presents challenges. High implementation and operational costs, the need for specialized technical expertise, complex data management requirements, and the necessity of cultural integration within existing coaching methodologies remain significant barriers. To address these issues, a holistic approach is required to extend beyond technological acquisition to encompass robust organizational management, continuous staff training, and strategic financial planning. Furthermore, longitudinal studies are needed to evaluate long-term sustainability, cost-effectiveness across diverse university contexts, and optimal sensor configurations tailored to specific sports and resource levels. It is also important to explore how sensor data can be leveraged to enhance academic outcomes and foster self-regulated training, aligning athletic programs with the broader educational mission of universities.

Material and design parameters for next-generation sensors can be identified on the basis of the results of this study. MXene-polymer composites provide high-precision strain sensing with minimal hysteresis, self-powered TENG networks enable energy autonomy, and hydrogel–elastomer interfaces ensure stable skin contact under dynamic conditions. Such a technical foundation is necessary to develop adaptive, high-fidelity sensor substrates capable of maintaining linear signal responses under extreme mechanical stress. By applying the advancement of sensor and materials engineering to sports science, robust, energy-efficient, and biocompatible sensor systems can be developed for real-time athletic monitoring. Further innovations in wearable technology and real-time sensor monitoring contribute to the development of safer, more efficient, and personalized university sports training environments.

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