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Integrated Wearable Sensor Technologies for Real-Time Sports Performance Evaluation

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Abstract

Wearable sensor technologies have revolutionized sports performance evaluation by enabling continuous, non-invasive, and real-time monitoring of athletes during training and competition. This narrative review synthesizes recent advances in integrated wearable sensor technologies for sports performance assessment, focusing on multimodal sensing, intelligent data integration, and artificial intelligence (AI)-driven analytics. The review covers key wearable sensor types, including biomechanical, physiological, biochemical, and textile-based sensors, along with their integration into smart wearable platforms supported by wireless communication and Internet of Things (IoT) technologies. Recent developments in machine learning for performance optimization, fatigue detection, injury prevention, and personalized training are also discussed. The findings highlight that integrating multiple sensing modalities with AI significantly enhances the accuracy and effectiveness of athlete monitoring. However, challenges such as motions, power limitations, user comfort, data privacy, and standardization remain. Future research should emphasize self-powered wearable systems, flexible electronics, edge AI, digital twins, and secure data management to enable next-generation intelligent sports monitoring.

Keywords

Wearable Sensors, Sports Performance Monitoring, Multimodal Sensing, Artificial Intelligence, Machine Learning

1. Introduction

The increasing need for objective, continuous, and personalized measurement of athletic performance has fuelled the advancement in wearable sensors technology, revolutionizing the contemporary sports sciences. Prior to the advent of wearable technologies, the assessment of the performance of athletes was based on laboratory physiology tests, video analyses, and coach observations, which could offer limited and sometimes inconsistent insights regarding the physiological and biomechanical responses of the athletes due to being conducted under controlled conditions and lacking the element of real-time measurements. Wearable sensors technology has addressed most of those issues, as it allows continuous, real-time and non-invasive measurement of various parameters related to the athletic performance [1] [2]. The development in wearable technology during the last two decades is tremendous; from basic pedometers to complex multi-modal sensors which not only can measure biomechanics, physiology, and bio chemicals parameters but also measure all three of these at once. The modern-day wearable consists of MEMS, flexible electronics, small bio-sensors, wireless communication units and intelligent AI algorithms. These sensors allow measuring a variety of parameters including: acceleration, kinematics of joints, heart rate, heart rate variability (HRV), electromyography (EMG), electrocardiography (ECG), skin temperature, respiratory rate, biomarkers of sweat, blood oxygen saturation (SpO_2), and global positioning system (GPS) data on movement [3]-[5]. The integration of multiple sensing modalities has significantly enhanced the capability of wearable devices to provide comprehensive assessments of an athlete's physical condition and performance during real-world sporting activities.

The growing number of the wearable technology market shows how significant wearable technology has become for the sports and health care sectors. As per the most recent research conducted on the market, the value of the worldwide wearable technology market was around USD 84 billion in 2024, which is expected to grow beyond USD 186 billion by 2030, having an approximate CAGR of 14% - 15%. Similarly, there is significant growth in the sports wearable market because of the increased use by athletes and sportspersons [6] [7]. Furthermore, more than 500 million wearable devices are estimated to be shipped annually worldwide, generating unprecedented volumes of physiological and biomechanical data that facilitate precision athlete monitoring and evidence-based coaching strategies [8]. Performance monitoring in real-time has gained importance due to the dynamic nature of sports and the influence that the physiology of an athlete, biomechanics, environment, and psychology have on performance. Continuous performance monitoring helps coaches and sports scientists monitor the workload, fatigue, efficiency of movements, cardiovascular performance, and the condition of recovery both during training and competing. Real-time data help make timely modifications to training loads, individual exercise prescriptions, and detect risks of injury. Wearable inertial measurement units can be used to monitor running biomechanics and asymmetry of movements, whereas wearable EMG can help understand muscle activation patterns related to fatigue. Sweat sensors can be used for the analysis of lactate, sodium, glucose, and pH levels [3] [6] [9]. The integration of these diverse physiological signals enables a more holistic evaluation of athletic performance than any single sensing modality alone.

However, even with all these improvements, there are still some challenges that traditional sports performance evaluation processes face. Traditional evaluation tools such as the motion analysis equipment, metabolic cart, force plate, and biochemical analysis usually involve complex instrumentation, expertise, and laboratory environment [10]. Furthermore, such techniques tend not to account for the physiological reactions of the athletes under real-life competitive circumstances. The optical motion capture system is known for its high level of accuracy but is prone to marker occlusions, limited volumes of measurement, and complicated calibration process. Similarly, periodic physiological measurements provide only occasional information about the state of an athlete [11]. Consequently, there is an increasing demand for integrated wearable systems capable of delivering accurate, continuous, and context-aware monitoring under unrestricted sporting environments.

Recent developments in flexible electronics, IoT, wireless communication, cloud computing, and artificial intelligence (AI) have greatly enhanced the capabilities of wearable. Unlike traditional wearable devices that use one sensor at a time, the future generation of wearable technology uses multimodal sensor fusion, which includes the fusion of movement sensors, physiological sensors, and biochemical sensors into one intelligent system. Machine learning and deep learning models used in AI allow for automated detection and analysis of activities, fatigue, risks of injuries, and individualized performance improvement [11]-[13]. These technological developments are driving the transition from passive data collection toward intelligent decision-support systems capable of delivering actionable insights for athletes, coaches, clinicians, and sports scientists.

For the purpose of this review, performance consists of quantitative performance factors and workload including such variables as speed, acceleration, power, efficiency of movement, techniques and endurance of an athlete. Fatigue is defined as an exercise-induced decrease in physiological or biomechanical functioning which can be estimated by changes in heart rate variability, EMG characteristics, kinematics, workload and corresponding factors. The term recovery means a process of restoring of the physiological and functional state after exercise and is assessed via trends in such parameters as resting heart rate, heart rate variability, sleep, movement and other recovery-related parameters. Injury risk means an estimate of the probability or increase in the susceptibility for injury due to certain physiological and biomechanical factors such as asymmetry in movement, joint load, progressive overload of workload, fatigue, recovery and so forth; it should not be understood as injury itself. It is worth noting that wearable sensors capture primary information of acceleration, angular velocity, pressures, electrical, optical, temperature data and biochemical parameters. Performance, fatigue, recovery and injury risk are high-level terms that are derived from sensors' output data.

Taking all these into account, this review offers a systematic summary on the integrated wearable sensor systems for real-time sports performance analysis. In this paper, firstly, the basic concepts and classification of various kinds of wearable sensors for biomechanical, physiological, biochemical, and environmental measurements will be introduced. Second, the latest progress in terms of the integration of multiple modalities, flexible platforms, wireless communications, and AI-based analytics will be highlighted for intelligent sports monitoring.

Continuous biochemical sensing using electrochemical analysis of lactate, glucose, cortisol, electrolytes, and pH levels in sweat and interstitial fluid is anticipated in the future generation of wearables. The information derived could help understand dehydration patterns, metabolic changes, stress, and exhaustion if combined with information from other biometric parameters. Translating sweat analysis information into relevant physiological information would necessitate accounting for sweat rates, sampling site selection, contamination, time delay, environment, and individual calibration [6] [9]. Through the discussion of recent advancements and open issues, the objective of this paper is to present a comprehensive picture to researchers, engineers, clinical doctors, and sports experts about future development of integrated wearable systems for precision sports performance analysis. **Figure 1** shows the architecture of a holistic wearable sensor system used for evaluating sports performance in real time. Modern-day wearable devices utilize various sensory capabilities that involve motion, physiological, biochemical, and flexible fabric-based sensors to constantly monitor the

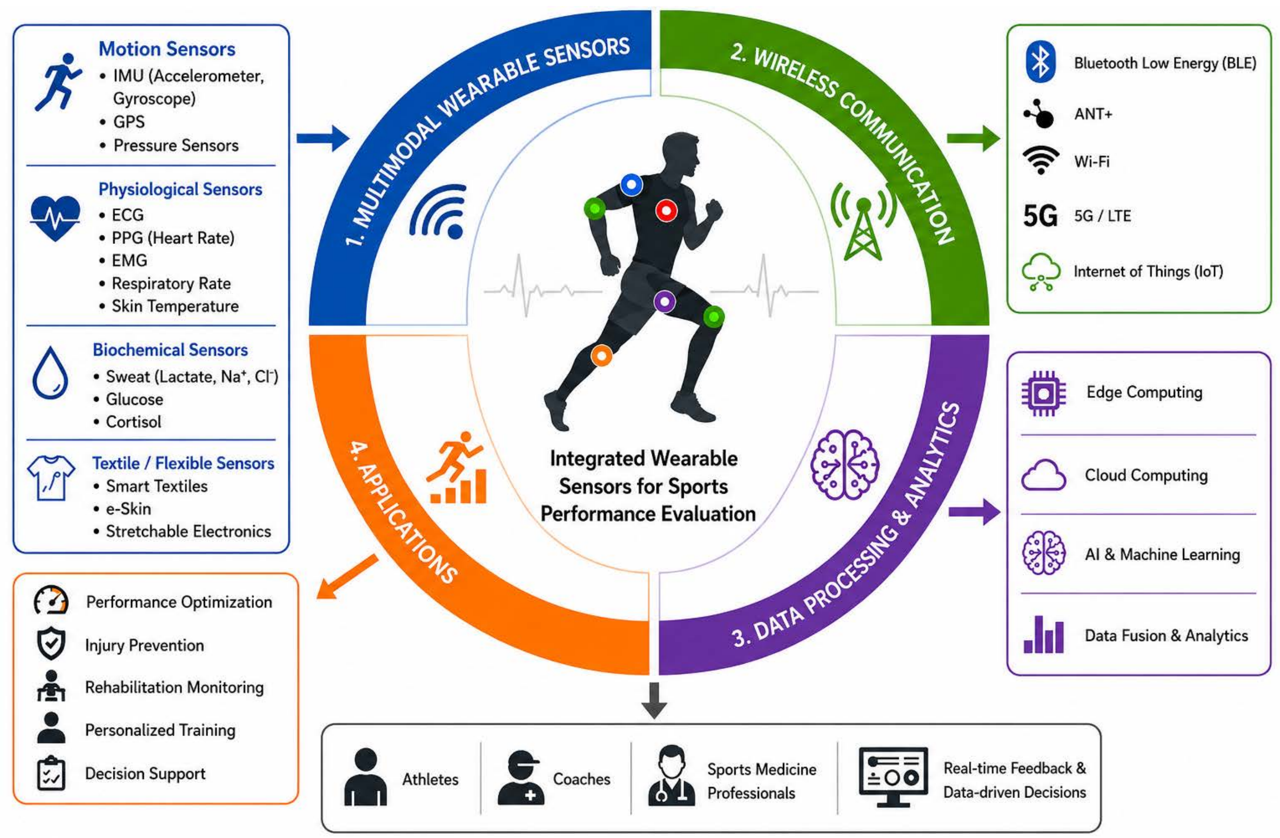

Figure 1. Overall architecture of an intelligent wearable sports monitoring system.

state of an athlete. The sensed data is transferred using wireless communication to edge and cloud computing infrastructures, which use artificial intelligence algorithms and sensor fusion techniques to make sense out of the raw data coming from sensors. Such systems provide a means for performance improvement, injury prevention and rehabilitation, training, and evidence-based decisions for athletes, coaches, and sports medicine experts. The subsequent sections discuss the components of a holistic wearable system with emphasis on sensing technologies for sports performance monitoring.

Literature Review Methodology

This article is represented as a narrative review which consolidates advances in wearable sensors technology for real-time performance evaluation of athletes in sports activities. Literature research was performed using the main scientific databases (Web of Science, Scopus, IEEE Xplore, PubMed, Google Scholar) that were chosen for identifying peer-reviewed scientific papers from 2015 until 2026, although some landmark studies earlier in time were included for contextual background. Search was conducted combining different sets of keywords corresponding to wearable sensors for real-time monitoring in sports and exercise science such as: wearable sensor, sport performance monitoring, inertial measurement unit (IMU), accelerometer, gyroscope, ECG, EMG, photoplethysmography (PPG), sweat biosensor, smart textile, sensor fusion, artificial intelligence, machine learning, digital health, and athlete monitoring. Boolean operators (AND/OR) were applied in searching the relevant articles in different databases.

The chosen literature was selected based on the following selection criteria: (1) peer-reviewed journal articles and comprehensive reviews; (2) papers concerning development of wearable sensing technologies in sports; (3) publications presenting principles of sensing, validating the sensors, integrating systems, applying artificial intelligence or performing applications in sports practice; (4) scientific papers written in English. Conference papers, editorial papers, patent applications and unrelated to wearable sensing sports papers were excluded but except when providing basic information regarding technologies.

2. Wearable Sensor Technologies for Sports Performance Monitoring

Nowadays, wearable sensor technology is considered a necessary tool to perform sports performance evaluation, since it allows obtaining continuous and reliable information about the athlete's state while conducting exercises or participating in competitions in a non-invasive way. The recent development in MEMS, flexible electronics, wireless communication, and artificial intelligence increased the level of accuracy and versatility of wearable sensor technology, which enables performing monitoring of biomechanical, physiological and biochemical parameters during training and competition without interfering with performance [5] [9] [14]. Wearable sensors play a significant role in monitoring sports performance as they offer continuous and non-invasive real-time data about physiological, biomechanical, biochemical, and environmental parameters. Based on the parameters monitored as well as the sensor technology used, the types of wearable devices reviewed here are divided into three main classes: 1) motion/biomechanical sensors, 2) physiological/biochemical sensors, and 3) flexible/textile wearables. The three different types of wearables offer supplementary data on athletes' locomotive functions, physiological conditions, metabolic reactions, and integration with comfortable wearable devices, thus facilitating a holistic assessment of sports performance. The major types of wearable sensors currently used for sports performance assessment and their corresponding applications are depicted in Figure 2 below. The subsequent subsections provide details about each sensor type.

Figure 2. Classification of wearable sensor technologies used for sports performance evaluation.

In contrast to traditional assessment techniques conducted in laboratory settings, wearable sensors enable collecting the data continuously in real-life environments, making the objective assessment of movement, physiological response and recovery possible. Current wearable sensor systems are equipped with several types of sensors that provide multimodal information and intelligent evaluation of performance. Sensor fusion technique allows increasing the reliability of measurements and providing a holistic view of the state of the athlete in terms of his/her physical condition, workload and performance. In addition, the development of wireless communication and IoT technologies provides the possibility of transmitting collected data and using artificial intelligence to evaluate it [4] [15].

Depending on the type of the principle of operation and the parameters being measured, the wearable used in sports performance evaluation can be divided into three main groups: 1) motion and biomechanics sensors that measure movements and forces exerted by the body; 2) physiological and biochemical sensors that evaluate cardiovascular, muscular, respiratory, thermal, and metabolic responses; and 3) flexible and textile-based wearable.

2.1. Motion and Biomechanical Sensors

The key components of wearable that enable performance tracking in sport are motion and biomechanical sensors which allow measuring quantitative and objective data about athletes' kinematics, posture, orientation, acceleration, angular velocities, and reaction forces during training and sport events. Wearable sensors are capable of collecting a great deal of data that allows evaluating an athlete's performance in terms of kinetics and kinematics in real-life environment which is a significant advantage compared to traditional motion capture systems which rely on using several high-speed video cameras and reflective markers and require being conducted in a controlled laboratory environment. The recent years' developments in micro-electromechanical systems and the emergence of wireless communication technologies make such devices increasingly popular in elite sport, rehabilitation, and recreational physical activity.

Currently, biomechanical monitoring systems make use of accelerometers, gyroscopes, IMUs, and pressure/force sensors which help to measure complementary data concerning linear acceleration, angular velocities, body orientation, joint kinematics, balance, gaits, and reaction force distributions. Such combination allows conducting an overall assessment of an athlete's movement quality, workloads, fatigue, and injury risks which makes such devices critical in evidence-based sports performance evaluations [14]. Recent wearable systems typically operate at sampling frequencies ranging from 100 to 1000 Hz, ensuring sufficient temporal resolution for capturing rapid movements such as sprinting, jumping, throwing, and racket swings [16].

The validity of wearable devices measuring biomechanics must be noted to have certain contextual dependencies, which is important. Values indicating accuracy, correlation, and error rate are highly dependent on the particular type of sensors or arrangement of wearable devices, body location of the device, measurement methodology, type of athletic activity, subject group, and reference system utilized for validation. In this regard, numerical values provided below should be understood in the context of the research papers mentioned.

- **Accelerometer**

The accelerometer sensor is one of the most common wearables in sport biomechanics due to its simple design, low energy consumption, small size, and high accuracy. The accelerometer measures linear acceleration, which is comprised of dynamic acceleration created by body movements and static acceleration produced by gravity. Modern wearable accelerometers are MEMS devices, and their operation principle is related to a proof mass displacement when the sensor is accelerated. This displacement is transformed into an electrical signal via different techniques such as capacitive, piezoresistive, and piezoelectric sensors [17]. Wearable accelerometers come in three forms, namely, single axis, double axis, and triple axis accelerometers. The preferred accelerometer used in sports is the triple axis accelerometer since it can measure acceleration on all three planes, *i.e.*, mediolateral (x), anteroposterior (y), and vertical (z). In commercial MEMS accelerometers, the measurement ranges lie in the range of ±2 g to ±16 g. Some accelerometers developed specifically for high-impact sports like tackling, boxing, and gymnastics have measurement ranges up to ±200 g [10] [18] [19]. The current wearable accelerometers have resolution less than 1 mg, noise density of 20 to 150 $\mu g/\sqrt{Hz}$, and sample frequency from 100 to 1000 Hz [20].

Studies on the validation of selected running-related parameters have demonstrated good agreement between the accelerometric data and laboratory reference measures for certain experimental protocols; yet, the correlation and error are subject to the sensor location, running task, computational algorithm, and reference method chosen. Thus, the outcomes from those studies cannot be considered universal values for the accuracy of using accelerometers in sports applications [10]. The same applies in football and rugby where accelerometers attached to players' bodies measure players' workload in terms of total distance travelled, high-intensity acceleration and deceleration, and collisions. Jumping sports, including volleyball and basketball, make use of accelerometers to evaluate jump height, landing technique, and symmetry of the lower limbs. Jump height calculations using algorithms based on the vertical acceleration pattern produce errors less than 3% - 5% when compared with measurements from force platform, thus indicating that accelerometers could be used in assessing performance in such sports [21]. Additionally, accelerometers have proven useful in swimming, cycling, skiing, tennis, golf, and cricket for stroke analysis, pedalling rate, swing characteristics, bowling actions, and body posture while in motion [22].

In addition to measuring performance, accelerometers have proven to be useful instruments in fatigue detection and injury prevention. Fatigue generated from exercise usually affects the biomechanics of movement through increased variability of motion, decreased impact dampening, and change in stride symmetry. The continuous measurement using accelerometers helps detect such changes in the biomechanics of movements at an early stage so that coaches can alter the intensity of training before reaching an exhausted state. For instance, running smoothness and mediolateral acceleration variability have been linked to an increased incidence of injury among endurance athletes [23]. Asymmetrical acceleration can also be used in monitoring ACL reconstruction or lower limb injuries [24]. Recent improvements in artificial intelligence have greatly improved the analytical potential of accelerometers worn on the body. SVM (Support Vector Machines), random forests, CNN (Convolutional Neural Networks), and LSTM networks can automatically classify complicated movements, identify activities typical for particular sports, calculate exercise intensity, and predict fatigue with high precision. Deep learning models based on data from tri-axial accelerometers reached the level of activity recognition of over 95% and decreased dependency on manually designed biomechanical features [25]. These technological innovations are making possible a shift in the role of wearable devices from merely tracking tools into smart platforms that can provide performance feedback.

However, despite the benefits provided by accelerometers, there are certain limitations associated with the use of accelerometers alone. Due to their nature, accelerometer measurements include both gravitational and motion-related accelerations, and thus separating body orientation from movement becomes problematic, especially when it comes to fast multidirectional movements. Additionally, signal drift, vibrations, alignment issues, and soft tissues movement may lead to errors in measurements, especially in impact-based sports [26]. Furthermore, accelerometers are unable to provide information about rotation, which limits their ability to detect the full range of kinematics of joint movement. For all of these reasons, accelerometers are often combined with gyroscopes and magnetometers in order to form an IMU, which allows for more accurate measurement of body orientation and movement dynamics with the help of sensor fusion techniques [27].

- **Gyroscopes**

Though the accelerometers give out data about the linear acceleration of a body, they cannot directly measure the rotational motion of the body. However, the role played by the gyroscope is the same in the sense that it can measure the angular velocity along one or several perpendicular axes. This helps to calculate the posture, rotational movement, and joint rotation during physical exercises. Similar to accelerometers, current gyroscopes are mainly MEMS-based and use the Coriolis force developed by the vibration of a proof mass to estimate angular velocity [17]. The small size, low power consumption, and sensitivity of MEMS gyroscopes have made them an integral part of modern motion sensors. Commercial wearable gyroscopes are typically available as single-, dual-, and tri-axial configurations, with tri-axial devices being the most widely adopted for sports applications. These sensors commonly operate within angular velocity ranges of ± 125 to $\pm 2000^\circ\ s^{-1}$, although specialized systems designed for high-speed sporting activities such as baseball pitching, cricket bowling, tennis serves, and golf swings may extend to $\pm 4000^\circ\ s^{-1}$. Sampling frequencies generally range between 100 and 1000 Hz, allowing precise capture of rapid rotational movements without aliasing effects [20] [28]. Recent MEMS gyroscopes exhibit bias instability below $10^\circ\ h^{-1}$, angular random walk values of 0.01° - $0.1^\circ\ \sqrt{h^{-1}}$, and power consumption of only a few milliwatts, making them well suited for prolonged wearable applications [19].

Because of the ability of gyroscopes to measure the magnitude of rotational movements, gyroscopes have been used in biomechanical analysis of various sporting activities. In running, the angular velocity data from the gyroscopes give precise information on joint rotation, trunk stability, and foot placement during different phases of running [16]. The measurement helps in detecting improper running techniques, over-pronation, and abnormal movement associated with fatigue or injuries. For instance, validation of gyroscope measurements taken from sensors attached on the trunk and pelvis during sprint running and changes in direction showed that the error rate is around 3˚ - 5˚ with respect to the measurement setup that was used for the experiment [29]. Thus, these figures need to be understood against the particularities of sensor positioning, movement type, and validation process. Gyroscopes are an indispensable tool used in analysis of the swing and throwing motions of rotational sports like golf, tennis, baseball, and cricket. For instance, wearable gyroscope technology is able to measure angular speeds up to 1000˚ s^{-1} in the case of golf swings and allows the analysis of club head speed, swing rate, and sequence of pelvic and trunk rotations [30]. At the same time, in sports like cricket and baseball, gyroscope measurements of shoulder and forearm rotation allow a detailed assessment of the bowling and pitching actions with the goal of optimizing the technique and minimizing excessive joint stress leading to overuse injuries [10]. In gymnastics, skiing, and figure skating, gyroscopes are widely used for measurement of body orientation in the air.

Although there are many benefits of gyroscopes, it should be noted that these sensors are prone to errors through accumulation of integration. In other words, due to the fact that angular displacement is obtained through integration of angular velocity readings over time, minor biases accumulate and cause orientation drifts. The temperature changes, vibrations, and instability of the sensor bias can also affect accuracy of measurements, especially when recording lasts for a long time period. Therefore, gyroscopes are rarely used as single sensors in wearable sports applications.

- **Inertial Measurement Units (IMUs)**

The shortcomings present in motion sensors have led to the creation of Inertial Measurement Units (IMUs), which are now the most technologically advanced devices used in biomechanical monitoring of human movement. An IMU contains a three-dimensional accelerometer and three-dimensional gyroscope, possibly together with a three-dimensional magnetometer, all in one unit that can simultaneously detect linear accelerations, angular velocities, and orientation of the magnetic field. By combining the measurements of these different types of sensors through sensor fusion, IMUs are able to accurately detect body posture, joint kinematics, location, and motion paths. Common modern wearable IMUs incorporate either a 6-axis (accelerometer + gyroscope) or a 9-axis (accelerometer + gyroscope + magnetometer) arrangement. Consumer-grade IMUs targeted at sports applications usually feature sampling rates ranging from 100 to 1000 Hz, whereas advanced research-grade units can be over 2000 Hz for explosive athletic actions. Common accelerometer dynamic ranges are in the range of ±2 to ±16 g, while gyroscope dynamic ranges range from ±250 to ±2000˚ s^{-1}, which is enough to cover all sporting activities [10]. With recent developments in MEMS manufacturing, it became possible to design IMUs that weigh less than 20 g, making their integration into clothing, shoes, bands, helmets, and patches inconspicuous [2].

The biggest strength of IMU is its capability of creating three-dimensional representation of human movement with the help of sensor fusion algorithms. There are various algorithms that include Kalman filter, EKF (Extended Kalman Filter), complementary filter, Madgwick filter, and Mahony filter to determine orientation by combining the values of acceleration, angular velocity, and magnetic fields and minimizing the impact of any kind of drift or noise [31]. These computational algorithms provide significant improvement in the precision of biomechanical analysis as compared to accelerometers and gyros alone. IMUs have emerged as some of the most flexible wearable devices for evaluating sports performance. IMUs offer a comprehensive assessment of stride length, stride rate, contact time, vertical displacement, limb asymmetry, and joint angles of the lower extremities for runners and athletes. There are various validation studies that show a high level of correlation (>0.95) and error <5˚ in measuring joint angles compared to an optical motion capture system [27]. Their portability makes them ideal for use in training outside the lab environment.

Within team sports like football, rugby, hockey, and basketball, the use of wearable IMUs is widespread for the calculation of external load through acceleration, deceleration, direction changes, number of jumps, collision forces, and movement of the players overall. Such parameters help in adjusting training intensity, assessing playing performance, and detecting too much mechanical load which might lead to injuries [10]. The same applies for rehabilitation, as continuous monitoring of symmetry of movement and range of motion of joints helps in assessing the recovery from musculoskeletal injuries. IMU's integration with artificial intelligence has extended their applications. Machine learning models, which are developed on high dimensional data from IMUs, are able to classify sports-related activities, determine movement skills, assess the level of physical activity, predict exhaustion, and recognize injury-susceptible movements. In fact, some deep learning-based models that include CNNs and LSTMs have demonstrated accuracy levels greater than 95% - 98% for activity recognition, indicating significant capabilities of intelligent IMUs [13].

However, despite the development mentioned above, IMUs are still faced with some technical issues. For example, the presence of soft tissue s, magnetic interference, misalignments, cumulative integrations errors, and placement problems can lead to decreased measurement accuracy especially during dynamic and contact sports [32]. In addition, the constant acquisition of high-frequency information results in increasing the computational complexity, memory needs and battery drainage, thus constraining long-term use. The current research is therefore aimed at improving algorithms of sensor fusion, calibration processes, low-power electronics and edge-AI technology [26]. Thus, IMUs are likely to stay the base of future intelligent performance tracking systems due to their ability to conduct comprehensive biomechanical analysis under unrestricted sports conditions.

- **Pressure and Force Sensors**

Force and pressure sensors are crucial wearable devices used in biomechanics to determine the physical interaction between athletes and their environment. In contrast to accelerometers and gyroscopes, which derive movement from kinematic measurements, force and pressure sensors provide information regarding external forces like plantar pressure, ground reaction force (GRF), grip force, and joint loads. Under regular walking conditions, the maximum vertical GRF is about 1.0 - 1.2 body weight (BW); however, it can be increased up to 2 - 3 BW during running and more than 4 - 6 BW during jumping and landing [33] [34]. The most prevalent sensing techniques employed in wearable pressure sensors include piezoresistive, capacitive, piezoelectric, and force-sensitive resistor (FSR). Piezoresistive pressure sensors operate based on resistance changes and have been highly popular due to their easy manufacturing process, wide sensing ranges, and flexibility. Capacitive sensors measure pressure through changes in capacitance among deformable electrodes and have higher sensitivity, reduced hysteresis, and enhanced stability over time compared to piezoresistive sensors. Piezoelectric sensors work through electric charges produced when subject to dynamic loading conditions and are especially useful in measuring sudden impacts. The use of FSR sensors in commercial plantar pressure sensors is attributed to the thin design and low manufacturing costs despite poor linearity and signal drift issues [35].

The study of plantar pressure is one of the oldest and most developed uses of wearable pressure sensing in sports. Currently, pressure-sensing insoles are used to sample pressures in the range of 100 to 200 Hz, while scientific equipment can go as high as 500 Hz, allowing constant measurement of foot loads on walking, running, jumping, and changing directions rapidly. The equipment analyzes parameters such as foot strike pattern, centre of pressure trajectory, duration of stance phase, symmetry of strides, and distribution of loads on the foot sole [33]. Pressure sensors are just as useful in assessing athletic performance in terms of explosive motions. In the case of sprinting, contact times on the ground are normally in the order of 80 - 150 ms, while counter-movement jumps have a contact time of around 200 - 300 ms, implying that sensors must have high temporal resolution to adequately quantify impact loading, rate of loading, jump kinematics, and bilateral asymmetry. The quantification of landing technique is vital when trying to understand movement techniques with a high risk of ACL injuries [33] [36].

Flexible pressure sensors have found applications in wearable for monitoring grip forces and joint loading while performing certain physical actions, like playing tennis, golf, rowing, baseball, rock climbing, and rehabilitation exercises. Thanks to recent advancements in materials like graphene, carbon nanotubes (CNTs), MXenes, metallic nanowires, and conductive polymers, wearable pressure sensors became much more sensitive, flexible, responsive, and durable enough to be used for monitoring various pressures in applications associated with sports biomechanics and healthcare [35]. In addition, the use of wearable pressure sensors in combination with IMUs, EMG, and other physiological sensors has made possible a comprehensive assessment of biomechanics through multimodal wearables. In spite of considerable technological advances, there are certain hurdles to be overcome before such technologies can be used in high-performance sports. The issues of sensor hysteresis, calibration drifts, temperature dependence, fatigue and inability to accurately measure multidirectional shear stresses still hamper accurate measurements. Future developments in this field will be aimed at creation of self-powered, stretchable and resilient sensing materials along with artificial intelligence-based software for automatic calibration, signal processing and personalized biomechanical analysis.

In order to provide a comparative study on the primary sensors for measuring motion and biomechanics parameters in sports performance evaluation, **Table 1** lists the parameters that each type of sensor measures, their operational range, application in different sports, merits, demerits, and some references. This can aid in selecting the most suitable sensor for biomechanical analysis.

Table 1. Comparison of motion and biomechanical wearable sensors for sports performance evaluation.

Sensor Type	Measured Parameter	Typical Quantitative Range	Sports Applications	Advantages	Limitations	References
Accelerometer	Linear acceleration	Typical measurement ranges: ±2 to ±16 g; sampling frequencies 100 - 1000 Hz depending on application	Running biomechanics, gait analysis, jump height estimation, impact detection, activity recognition	Lightweight, low power consumption, inexpensive, suitable for long-term monitoring	Cannot independently determine orientation; susceptible to vibration and impact noise	[10] [27]
Gyroscope	Angular velocity	Typical measurement ranges: ±250 to ±2000° s^{-1}	Joint kinematics, golf swing, throwing, cycling, balance assessment	High accuracy for rotational motion	Angular drift accumulates during integration; higher power consumption than accelerometers	[10] [27]
Inertial Measurement Unit (IMU)	Linear acceleration, angular velocity and orientation	Usually combines 3-axis accelerometer + 3-axis gyroscope, often with a magnetometer; sampling frequencies commonly 100 - 500 Hz in sports monitoring	Sprint analysis, jump assessment, gait analysis, team-sport workload monitoring, rehabilitation	Comprehensive motion analysis, portable, suitable for field measurements	Sensor fusion required; magnetic disturbances affect orientation estimation	[10] [27] [31]
Pressure/ Force Sensor	Plantar pressure, force distribution, centre of pressure	Plantar pressures during walking and running typically range from 200 - 1000 kPa, depending on gait phase, footwear and activity	Gait analysis, running biomechanics, balance assessment, injury prevention, footwear evaluation	Direct measurement of plantar loading, portable, suitable for field use	Calibration drift, sensor wear, localized pressure measurements	[33] [35]

As can be seen from **Table 1**, inertial sensors, such as accelerometers, gyroscopes, and IMUs, dominate the field of movement analysis using wearable technology due to their portability, high sampling rates, and capability to measure the kinematics of the body during real-life sports situations. In contrast, pressure sensors collect localized data about the kinetics through the measurement of foot pressure and its distribution. As a result, multimodal sensors that combine both inertial and pressure sensors are increasingly used for more comprehensive biomechanical analyses.

2.2. Physiological and Biochemical Sensors

Even though biomechanical and motion sensors measure external movement and loading, they fail to determine an athlete's physiological state internally. The role of physiological and biochemical sensors is to provide information on cardiovascular, neuromuscular, thermal, respiratory, and metabolic responses. The modern wearable technology has the capability of monitoring different physiological parameters, such as ECG, PPG, EMG, body skin temperature, respiration, and sweat biomarkers [37]. The portable devices give real-time feedback concerning heart rate (which varies between 40 - 60 bpm in conditioned endurance athletes, and up to 180 - 200 bpm during maximum activity), heart rate variability (HRV), breathing rate (ranging from 12 - 20 b/min under resting conditions to 40 - 60 b/min during strenuous activity), skin temperature (generally ranging from 32˚C - 35˚C), and perspiration, which can exceed 1 - 2 L per hour during prolonged high-intensity workouts. Monitoring these variables continuously enables an evaluation of cardiovascular stress, thermoregulation, hydration levels, electrolytes balance, exhaustion level, and post-training recovery, hence enabling personalized training protocols and decreasing the hazards of dehydration, overtraining, and sports injuries [37] [38].

The sweat analysis data needs to be approached carefully, though. The electrolyte, lactate, glucose, cortisol, and any other analyte content in sweat cannot necessarily indicate quantitative body water and overall metabolism state. Those levels can change depending on the local sweat production rate, anatomical point of collection, physiology of sweating glands, contaminants present on the skin surface, evaporation rates, and environmental factors, as well as due to a time delay between physiological changes in blood or interstitial fluids and appearance in sweat. Individual differences make application of uniform thresholds problematic. Thus, the role of sweat-derived biomarkers is limited to being an auxiliary physiological indicator which would require individual calibration and other data [3] [37] [38].

Recent advancements in the field of flexible electronics, MEMS, stretchable conductor, skin-compatible devices, and microfluidic technologies have made possible the fabrication of conformable wearable sensor systems with excellent mechanical flexibility and long-term skin compatibility. The sensors have the ability to continuously collect biochemical and physiological information without interfering with the athletic activities and enable wireless communication for real-time monitoring. In addition, the combination of wearable sensors with BLE connectivity, IoT networks, cloud technology, and machine learning algorithms allows multimodal information fusion systems that provide the integration of biomechanical, physiological, and biochemical information. The machine learning algorithm can help in merging the information from ECG, EMG, PPG, IMUs, temperature sensors, and sweat biosensors in order to assess the training load, fatigue development, recovery level, hydration, and injury risks [38] [39].

For this reason, physiological and biochemical sensing has emerged as an integral part of the future generation of wearable technology for the assessment of athletic performance. The rest of this chapter will review the sensing mechanisms, latest technological advancements, and application in sports of several wearable physiological and biochemical sensors, including ECG, PPG, EMG, temperature sensors, sweat biomarker sensors, and respiratory sensors. Although biomechanical sensors mainly measure external movements, physiological and biochemical sensors contribute additional data about the internal status of the body while performing exercises. Table 2 below is a comparison of the major physiological, biochemical, and flexible wearable sensing technologies, along with their parameters, measurement ranges, and uses in sports, strengths, weaknesses, and relevant literature sources.

Table 2. Comparison of physiological, biochemical and flexible wearable sensors for sports performance evaluation.

Sensor Type	Measured Parameter	Typical Quantitative Range	Sports Applications	Advantages	Limitations	References
ECG	Cardiac electrical activity, heart rate, HRV	Heart rate: 40 - 60 bpm (trained athletes at rest); 180 - 200 bpm during maximal exercise	Exercise intensity monitoring, cardiovascular assessment, recovery analysis, fatigue monitoring	Gold standard for cardiac monitoring; excellent temporal resolution	Motion artefacts; electrode placement required	[39] [40]
PPG	Blood volume pulse, heart rate, oxygen saturation	Heart rate: 40 - 200 bpm; arterial oxygen saturation generally 95% - 100% in healthy individuals	Wrist-worn heart-rate monitoring, recovery assessment, training load estimation	Comfortable, low cost, easily integrated into watches and wristbands	Motion artefacts and ambient light interference	[39] [40]
EMG	Muscle electrical activity	Surface EMG amplitude typically 0 - 10 mV; frequency content 20 - 450 Hz	Muscle activation analysis, fatigue assessment, rehabilitation, strength training	Direct assessment of neuromuscular function	Sensitive to electrode placement, sweat and muscle cross-talk	[39]
Temperature Sensor	Skin temperature	Typical skin temperature 32˚C - 35˚C under normal physiological conditions	Heat stress monitoring, thermoregulation, recovery evaluation	Non-invasive, continuous monitoring	Strongly affected by ambient temperature and airflow	[39]

Continued

Respiration Sensor	Respiratory rate and breathing pattern	Resting respiratory rate: 12 - 20 breaths min^{-1}; vigorous exercise: 40 - 60 breaths min^{-1}	Endurance monitoring, ventilatory threshold estimation, fatigue detection	Continuous respiratory assessment using chest straps or smart garments	Motion artefacts during vigorous activity	[39]
Sweat Biosensor	Sweat rate, Na^+, K^+, Cl^-, lactate, glucose, pH	Sweat rate during exercise: 0.5 - 2.0 L h^{-1}; sweat sodium concentration typically 10 - 70 mmol L^{-1}	Hydration assessment, electrolyte monitoring, metabolic analysis, heat stress evaluation	Real-time, non-invasive biochemical monitoring	Sweat composition varies with individual physiology and environmental conditions	[3] [40]
Smart Textile	Integrated physiological and biomechanical signals	Wash durability reported up to 25 - 50 laundering cycles for advanced e-textiles (device dependent)	Smart shirts, socks, compression garments, rehabilitation clothing	Comfortable, washable, unobtrusive monitoring	Conductive yarn degradation, manufacturing complexity	[41]
Electronic Skin (E-skin)	Pressure, strain, temperature, electrophysiological and biochemical signals	Device thickness typically tens to hundreds of μm	Continuous athlete monitoring, rehabilitation, human-machine interaction	Skin-conformal, lightweight, multifunctional sensing	Long-term adhesion and durability remain challenging	[41] [42]
Stretchable Electronics	Multimodal physiological sensing	Stretchability commonly exceeds 100% tensile strain for elastomer-based devices	Flexible patches, smart wearables, integrated health monitoring	Excellent flexibility and conformability	Power management and large-scale fabrication remain challenging	[40] [43]

As summarized in Table 2, wearable physiological and biochemical sensors have evolved from being simple single-parameter monitors into more complex devices which can monitor cardiac activities, neuromuscular activities, body temperature, breathing rates, dehydration, and biochemical indicators all at once. The latest breakthroughs in flexible electronics, smart textiles, and electronic skin technology have made continuous non-invasive multimodal monitoring more possible, comfortable, and mechanically adaptable. All of these will speed up the use of AI and wireless communication technologies in future generations of wearable devices.

2.3. Flexible and Textile-Based Wearables

The development of flexible materials and soft electronics has evolved the use of rigid wearable devices into flexible wearable devices embedded in textiles and capable of continuously tracking body movements and vital signs. In contrast with rigid wearable devices, flexible and textile-based wearables can conform well to the skin or clothing, thus minimizing motion s and making the device comfortable for long periods of exercise. Flexible and textile-based wearables have conductive yarns, flexible circuits, stretchable sensors, and wireless communication units to track body movements, physiological parameters, and environment data continuously without interfering with athletic activities. Recent advancements have made it possible to design wearable devices that sustain repeated deformations and remain stable for sensing [41] [42].

Smart textiles (e-textiles) are among the most rapidly evolving wearable devices in sports science, whereby conducting threads, embroidered electrodes, printed circuits, and flexible sensors are embedded directly in garments like compression shirts, shorts, socks, gloves, and sports bras. With the help of smart fabrics, it is possible to monitor simultaneously ECG, EMG, respiration, body posture, joint movement, and muscle activity without the attachment of multiple sensor devices to the skin. It has been shown that commercial and experimental e-textiles are capable of reliable physiological monitoring during running, cycling, and team sports, ensuring high comfort of the athletes. There are examples of washable textile sensors able to preserve their electrical properties after 25 - 50 washing cycles [41].

Electron skin (E-skin) is composed of ultra-thin sensor array systems that have been developed in such a way as to reproduce the mechanical characteristics of the human skin to monitor various physiological and biomechanical parameters. Modern E-skins can measure pressure, strain, temperature, electrophysiological parameters, and biochemical markers with high spatial resolution while keeping in direct contact with the skin. Conventional E-skins are thin enough, with thicknesses in the range of tens to hundreds of microns and similar values of Young's modulus (in the range of 10 - 150 kPa) to those of human skin [42].

Stretchable electronics add another layer to wearable capabilities by adding intrinsically stretchable conductors, elastic substrates, serpentine connections, and soft nanomaterials that retain their electrical characteristics despite undergoing large deformations. The latest generation of stretchable wearables can withstand mechanical deformations greater than 100% to 300%, allowing continuous measurement of physiological parameters such as ECG, EMG, pulse waves, body temperature, and sweat components. Graphene, carbon nanotubes, MXenes, conductive polymers, and liquid metals have helped improve electrical and mechanical properties, along with biocompatibility, facilitating reliable wearable electronics for sports assessment. In spite of impressive progress, the wearables sector, particularly those that are flexible and textile-based, is still encountering difficulties regarding the durability of sensors in the presence of repetitive washing and mechanical loads, signal stability, energy supply, and large-scale fabrication. Thus, current scientific efforts are directed toward developing self-powered sensing, energy harvesting, multifunctional textiles, and AI-powered signal processing for future wearable devices for performance monitoring.

Despite varying sensing principle and physiological parameter, all wearable sensors aim to transform physical, physiological, or biochemical signals into measurable electrical signals, which may then be used in monitoring athletes in real time. The principle of motion sensors involves detecting body movements through variation in the inertial characteristics, physiological sensors work by measuring bioelectric or optical signals from the human body, biochemical sensors use electrochemical reactions to measure specific biomarkers, while flexible strain sensors detect body deformation by making use of stretchable conductors. It is important to have an understanding of the above basic principles of sensor operation in order to select suitable wearable sensors for specific sport applications. Figure 3 below demonstrates the operation principles of selected wearable sensors applied in sports performance assessment.

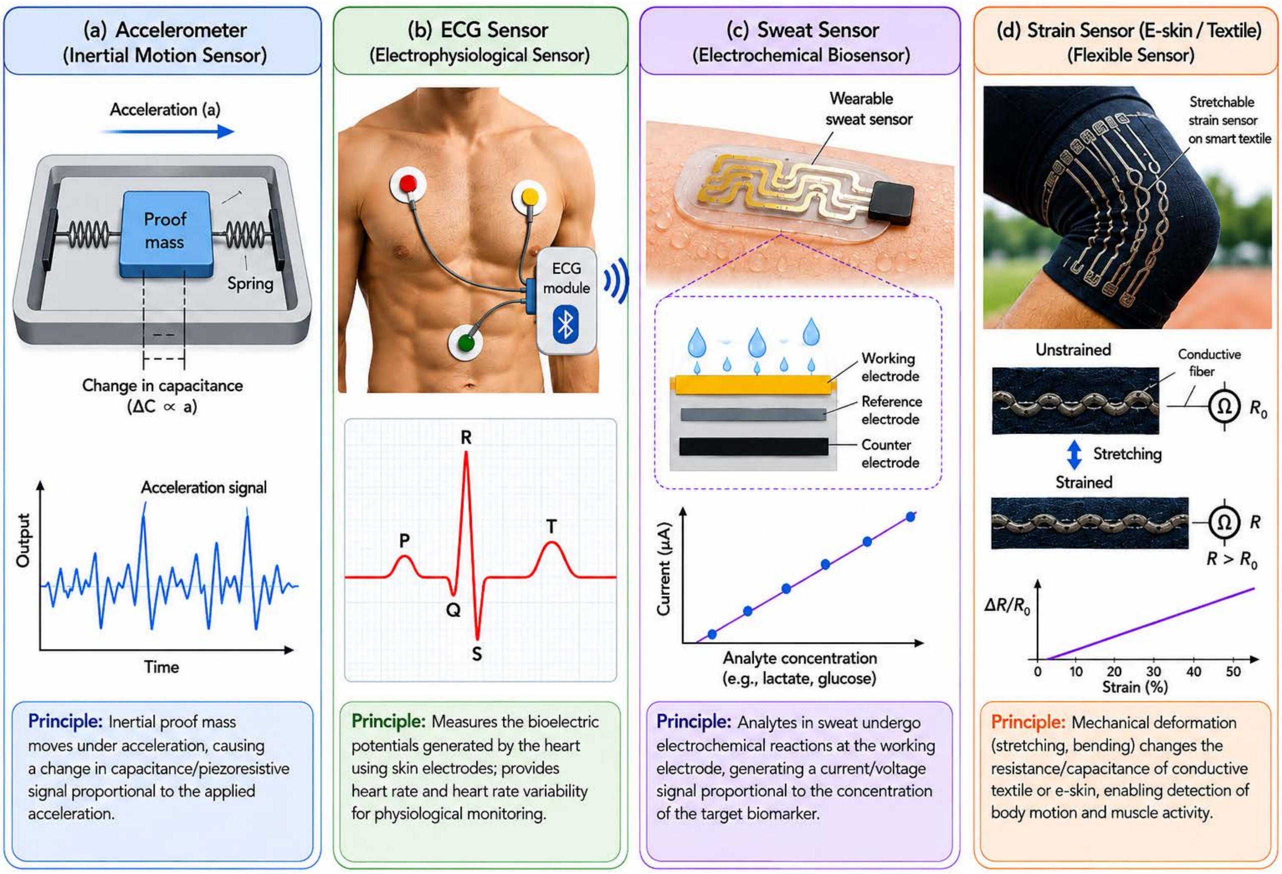

Figure 3. Working principles of representative wearable sensors employed in sports performance evaluation. (a) Inertial accelerometer measuring body motion through displacement of a proof mass, (b) ECG sensor acquiring cardiac bioelectrical signals using skin electrodes, (c) electrochemical sweat sensor detecting biomarkers such as lactate and glucose, and (d) flexible strain sensor monitoring body deformation through changes in electrical resistance. These sensing mechanisms collectively enable continuous biomechanical, physiological, and biochemical monitoring during athletic training and competition.

3. Integrated Wearable Systems and Intelligent Data Analytics

The development of new wearable sensors for the assessment of sport performance has brought about the transformation of sports performance analysis from a single parameter assessment system to an intelligent system that is able to assess the performance of athletes in real life. Despite the fact that individual wearable sensors can provide important data on different biomechanical and physiological parameters, athletic performance involves a complicated relationship between movement, physiology, neuromuscular activation, metabolism, and the environment [5] [9]. The incorporation of inertial sensors, pressure sensors, ECG, PPG, EMG, breathing, temperature, and sweat sensing creates large amounts of varied data that cannot be adequately analyzed using traditional methods alone. The evolution of technology like sensor fusion, the Internet of Things (IoT), wireless networking, cloud computing, and artificial intelligence (AI) has thus become crucial in converting sensor data into valuable information for performance enhancement, fatigue analysis, injury prevention, and personalized training [44] [45].

AI has improved wearable technology even more by helping in automatic feature extraction, activity recognition, prediction, and decision making. On the other hand, new health technologies such as edge computing, cloud analytics, digital twin technology, and remote athlete monitoring have been developed to take wearables beyond just sensing to a full-fledged intelligent, connected sports health system [46] [47]. This section will outline the technologies that drive intelligent wearables for sports performance assessment. Section 3.1 outlines some of these technologies that include multimodal sensor fusion, sensor fusion techniques, IoT wearables, and wireless communications. In section 3.2, emphasis is placed on the use of artificial intelligence techniques such as machine learning, deep learning, edge artificial intelligence, fatigues monitoring, and injury prediction. Finally, section 3.3 outlines digital health technologies such as real-time monitoring of athletes, cloud computing technologies, digital twin, and remote coaching among others.

3.1. Multimodal Sensor Integration

The wearable systems of today have transformed from being simple machines to complex machines which are able to monitor various physiological and biochemical parameters at once. This helps in creating a better picture of the physical state of the athlete because different sources of data work together to increase reliability [5] [44]. Individual wearable sensors offer vital yet partial information about the physiological and biomechanical condition of an athlete. In order to gain a holistic view on the sports performance of a person, the data obtained from various sensing modalities including inertial, physiological, biomechanical and biochemical sensors are used in combination through a multimodal sensor fusion approach. The sensor data undergoes a process of preprocessing and feature extraction followed by the use of data fusion techniques to combine the data. Furthermore, research systems make use of electrochemical sensors to analyze components of sweat like sodium, potassium, glucose, lactate, pH level, and cortisol [3] [5] [9]. Such tests offer additional data concerning the biochemical reactions in a local area when exercising; nonetheless, such readings cannot be considered as direct indicators of overall metabolism or the state of hydration or stress as they depend on various factors including sweat flow rate, collection site, time delay, environmental parameters, and individual characteristics. Figure 4 shows the overall flow of the multimodal sensor fusion approach.

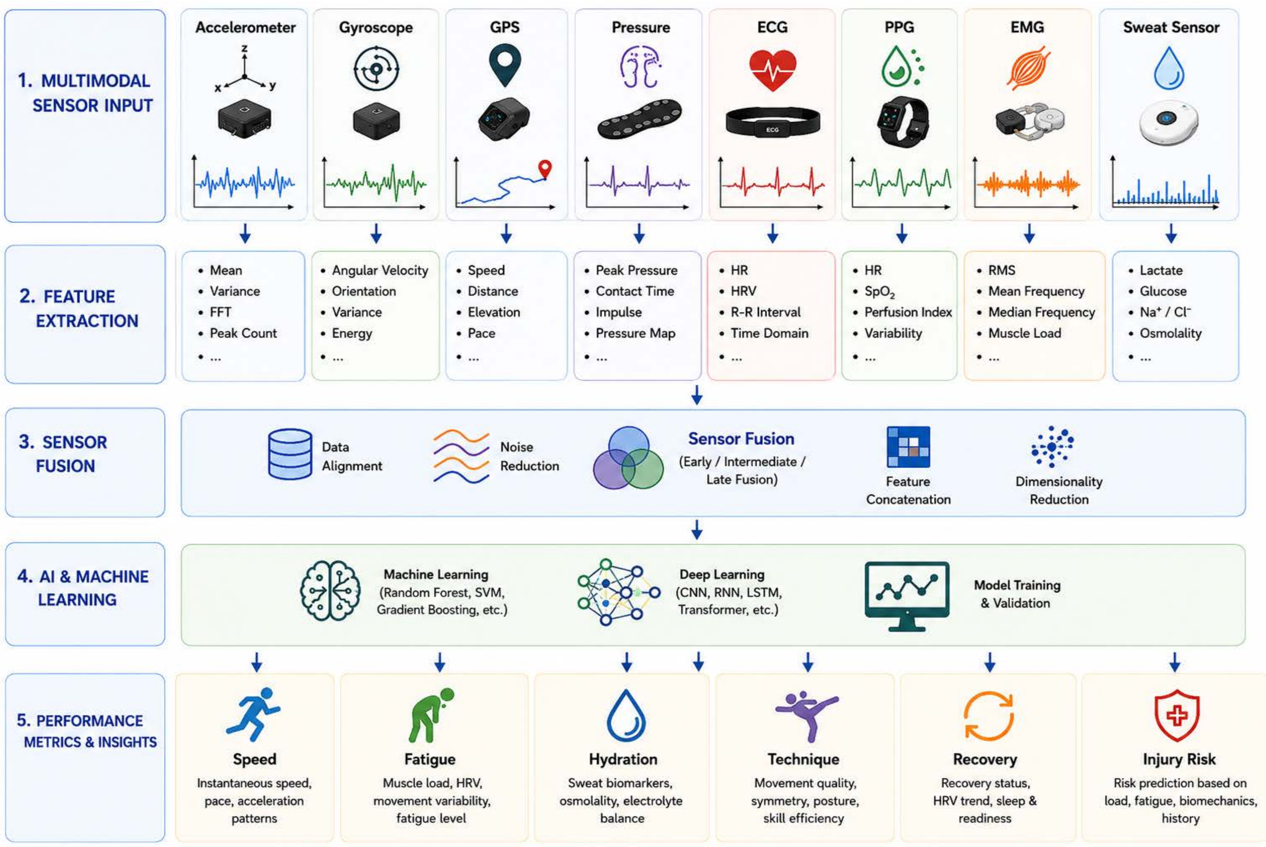

Figure 4. General framework of multimodal sensor fusion for intelligent sports performance evaluation. Data acquired from heterogeneous wearable sensors, including accelerometers, gyroscopes, GPS, pressure sensors, ECG, PPG, EMG, and sweat sensors, undergo feature extraction and multimodal sensor fusion before being analyzed using artificial intelligence and machine learning algorithms. The integrated framework generates high-level performance metrics such as speed, fatigue, hydration status, movement technique, recovery, and injury risk, enabling comprehensive athlete monitoring and personalized decision support.

- **Sensor Fusion**

Sensor fusion implies the process of combining data obtained from several sensors in order to acquire information which is more reliable and relevant than the one offered by each sensor separately. For example, in wearable monitoring of sports activities, IMUs, accelerometers, gyroscopes, magnetometers, pressure sensors, ECG, PPG, EMG, skin temperature sensors, and biochemical sweat sensors are often used together for the simultaneous recording of information about the biomechanics of movement, cardiorespiratory responses, muscular work, hydration state, and metabolism [3] [9]. The sensor fusion can be realized at the data, feature, or decision levels according to the needs of the particular task and its computational aspects. Recent review papers have demonstrated that sensor fusion leads to a much better robustness of human activity recognition and physiological monitoring systems and reduces their uncertainties. Sampling rate of wearable sensors depends on the physiological parameter being measured. Sampling rate of IMUs that measure gait and motion is in the range of 100 - 1000 Hz, ECG signals are acquired using sensors with a sampling rate of 250 - 1000 Hz and sensors that acquire EMG signals need a sampling rate of 1000 - 2000 Hz. Fusion of these high frequency signals create heterogeneous data which needs efficient synchronization and fusion algorithm [4].

- **Integrated Wearable Platforms**

The recent progress in flexible electronics has made it possible to design wearable integrated platforms by combining various sensors in one device. Commercially available smartwatches employ accelerometers, gyroscopes, PPG sensors, GPS, barometers, and skin temperature sensors to monitor physical activity and cardiovascular status continuously. The research platforms additionally employ electrochemical sensors that allow for monitoring the level of biomarkers in the sweat, including sodium, potassium, glucose, lactate, pH, and cortisol levels, providing a way to evaluate mechanical efficiency and physiological adaptation simultaneously [3] [5] [9].

- **IoT-Based Wearable Architecture**

IoT has become an essential element of the wearable ecosystem through providing seamless interaction between wearables, smartphones, edge processors, and cloud servers. In a standard IoT-driven wearable system, there exist four layers which include: (1) Sensing, which involves acquiring signals that are physiological and biomechanical in nature; (2) Communication, which entails the transmission of data using wireless communication channels; (3) Processing, which involves data processing either in the cloud or at the edge; and finally; (4) Application layer, which entails gaining insights for athletes, coaches, and clinicians through visualization interfaces [44] [45].

- **Wireless Communication Technologies**

Wireless communication systems are vital for sports performance monitoring in real time. The reason behind the widespread adoption of Bluetooth Low Energy (BLE) as the most commonly used communication protocol is its low power usage and great compatibility with phones and watches. The maximum physical data rate of BLE according to the Bluetooth Core Specification Version 5.4 is estimated to be 2 $Mb \cdot s^{-1}$ and the communication distance of around 100 m when operating under favourable conditions. On the other hand, ANT+ protocol is widely used for low-energy fitness equipment and Wi-Fi communication network is preferable for high-rate applications like video transmission from wearables. Moreover, emerging fifth-generation (5G) communication networks offer ultra-low latency and high capacity of the network, making them ideal for the near real-time transmission of multimodal physiological signals in remote sports training and telemedicine applications [4] [48] [49].

On the whole, multimodal sensor fusion serves as the basis for future generation wearable technologies for sports. The combination of heterogeneous sensors along with efficient sensor fusion techniques, together with IoT integration and wireless communication provides real-time, comprehensive, and precise evaluation of athletes' performance. Such systems not only increase measurement accuracy but also generate high-quality data sets that are necessary for advanced AI algorithms described below.

3.2. Artificial Intelligence for Sports Performance Evaluation

Wearable devices collect huge amounts of multimodal data from accelerometers, pressure sensors, electrocardiography, photoplethysmography, electromyography, global positioning systems, temperature, and biochemical sensors, which makes the application of artificial intelligence (AI) crucial for assessing sports performance. Support vector machines, random forest, decision tree, gradient boosting, k-nearest neighbour, and artificial neural network are commonly used machine learning (ML) methods that facilitate activity recognition, workload evaluation, movement classification, fatigue assessment, injury prediction, and athlete profiling. On the contrary, unsupervised ML methods like k-means clustering and hierarchical clustering uncover hidden trends during training adaptation and recovery through analysing data without labels. In contrast to traditional statistical analysis methods, ML methods are more appropriate for analysing nonlinear connections between biomechanical, physiological, and training-load factors [50]-[52]. The application of artificial intelligence has proven to be an important part of wearable sensing systems due to the possibility of converting massive amounts of heterogeneous sensor data into clinically and athletically significant data. In contrast to purely raw sensor data, AI systems use a particular approach involving signal preprocessing, feature extraction, machine learning, and prediction. Signal preprocessing helps to increase signal quality by filtering noise and s; at the same time, feature extraction allows extracting representative temporal, spectral, and statistical features of acquired signals. The next step involves analyzing the obtained features using machine learning and deep learning approaches for pattern recognition, athlete performance prediction, and personalized decision-making. The artificial intelligence pipeline used for sports performance assessment is presented in **Figure 5**.

Activity recognition: Several deep-learning techniques including CNNs, LSTMs, GRUs, and Transformer networks have been used for activity recognition based on wearable sensor measurements. Reviews of this approach have found that there is excellent classification performance in recognizing a set of predefined activities or physical-activity intensity categories [53] [54]. These studies do not assess prediction of fatigue or injury but deal with activity-recognition performance that varies according to the studied population, the sensor type and location, choice of the activity set, training-test split strategy, and the used performance measure. Refs. [53], and [54] represent a collection of several heterogeneous studies and the presented performance ranges cannot be taken as a validated performance level for athletes and sports setting.

Fatigue estimation: The problem of fatigue prediction is a different supervised

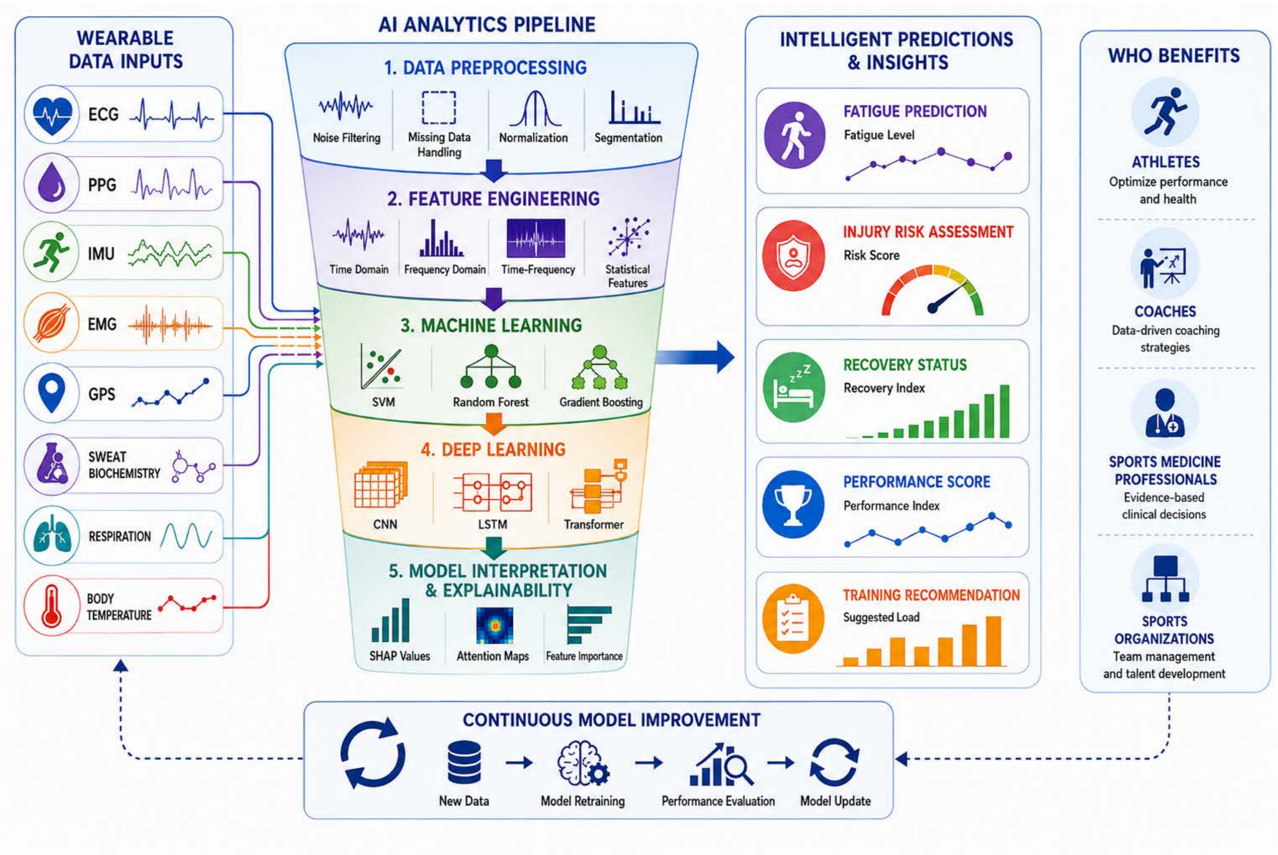

Figure 5. Flow diagram illustrating artificial intelligence pipeline to evaluate performance in sports using wearables. The direct sensor data collected from wearable devices is preprocessed and then analyzed through machine learning and deep learning approaches (SVM, RF, CNN, LSTM, and Transformer) in order to extract information related to high-level parameters such as performance, fatigue, injuries, recovery, and training advice.

machine learning problem because it involves predicting fatigue state or fatigued level as the target, rather than a class label of the performed activity [55]. Aguirre *et al.* [56], applied a random-forest technique for the classification of fatigue condition in repeated sit-to-stand exercise with the use of motion and physiological features with reported accuracy of 82.5%. It was an experimental exercise and rehabilitation study, and not a study of fatigue estimation in a specific sport. Jiang *et al.* [57] explored subject-dependent fatigue estimation based on body-worn IMU or force plate sensors during squatting, high-knee jacks, and corkscrew toe-touches exercises with an outcome variable of self-reported fatigue. Regression results based on CNN model were reported for these three exercises and correlations up to 0.89, 0.93, and 0.94, respectively, with the use of held-out data. These are results from within-study analysis and not from an external validation study in athletes.

Injury-risk prediction: The prediction of injuries is a more clinically important problem, as the target in this case is sports injury. Recently published by Dhahbi *et al.* [58] scoping review of 39 studies conducted with participation of athletic populations showed area under the curve values of approximately 0.82 - 0.95 for heterogeneous injury-prediction models. All the studies had substantial differences between each other in terms of sport, participants, predictors, outcome variables, and validation methods. Importantly, external validation has been rare in these studies and model transferability has been poorly validated. Injury-prediction performance cannot be compared to activity recognition or fatigue estimation and still cannot be taken as sufficient for the clinical decisions.

3.3. Digital Health and Athlete Monitoring

Wearable sensing technology combined with digital health has shifted athlete assessment from being conducted periodically in laboratory settings to constant, real-time health and performance evaluations. Contemporary wearables constantly monitor physiological, biomechanical, and biochemical data that can then be used for longitudinal assessment of adaptations, recovery, injuries, and general well-being of the athlete. Due to wireless communication and cloud-based services, such data can be transferred in a secure way to coaches, sports scientists, and medical personnel to inform practice decisions on both training and away-from-training sites [4] [5] [40]. The provision of real-time feedback is among the most useful applications of digital health in sports. The devices enable instant data collection on the heart rate, heart rate variability (HRV), SpO_2, body movement kinematics, sleep, and energy expenditure, which helps athletes and coaches adjust the level of training load according to the current physiological state. It was shown in recent systematic reviews that the use of wearable monitoring helps to enhance the training-load management process and detect excessive fatigue and insufficient recovery at an early stage, which lowers the risk of overtraining [40] [59]. Contemporary smartwatches and fitness wearables can track the heart rate using sampling rates of 25 - 128 Hz, while advanced ECG-enabled devices allow obtaining the ECG data with clinical-grade recordings of up to 30 s [4].

Modern advancements in digital health technologies have made wearable devices evolve into smart connected healthcare systems, which are able to continuously monitor athletes' health status. Contemporary wearable systems combine physiological, biomechanical and biochemical monitoring with smartphones, cloud and artificial intelligence technologies, allowing for the collection, analysis, and interpretation of data in real time. The use of digital twins, cloud analytics, edge AI, remote coaching and telemedicine technologies has enabled modern wearable systems to perform not only performance monitoring functions but also to provide predictive healthcare and precision medicine in sports. **Figure 6** shows the overall architecture of the digital health ecosystem, involving athletes, wearable systems, data analysis, doctors and personal trainers.

With cloud computing, it is now possible to have long-term storage, analysis, and integration of multimodal data from athletes. Cloud computing allows for longitudinal performance evaluation, analysis, and sharing of such data within multidisciplinary teams. When coupled with artificial intelligence, cloud computing enables automated analysis of trends, recovery, and individual performance

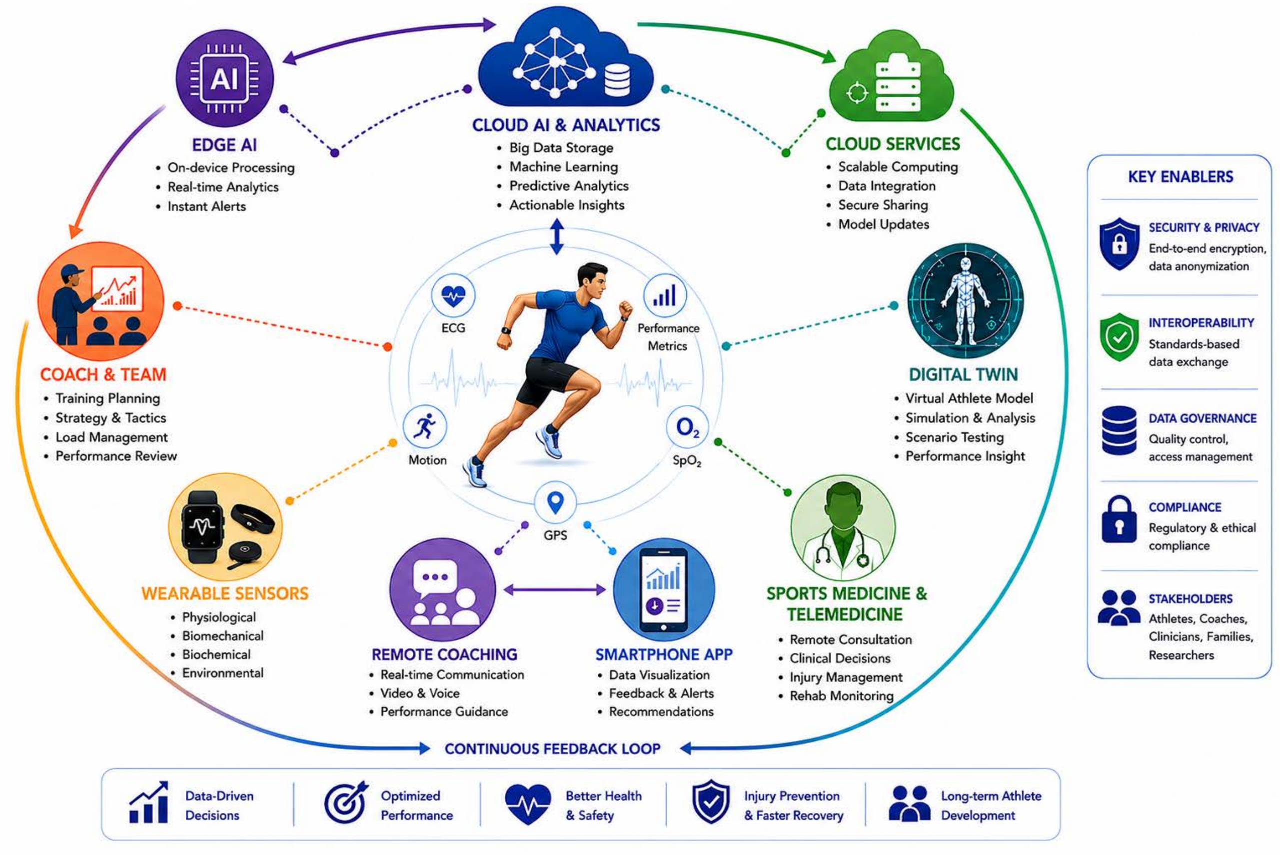

Figure 6. Digital health ecosystem for wearable-based sports performance monitoring, illustrating the integration of wearable devices, smartphones, cloud and edge AI, digital twins, remote coaching, telemedicine, and continuous feedback for personalized athlete management.

evaluation without overwhelming wearables with computation. However, it is important that cloud computing technology is accompanied by effective cyber security policies and data protection laws in order to ensure that athletes' personal data remain safe. A relatively new trend in digital sports medicine is the digital twin technology that stands for a constantly-updated computer model of the athlete that is based on sensor data, physiological parameters, medical history, and training results. The use of digital twins allows simulating physiological processes, predicting possible outcomes of performances, optimizing training approaches, and evaluating rehabilitation techniques without putting physical strain on athletes. Although it is at the initial stage of development, some recent publications point to the potential of digital twins for sports medicine applications [60] [61].

Remote coaching and telemonitoring using digital health technology has also been possible through which an athlete is able to get constant monitoring despite geographical constraints. By using wearable technology combined with applications on smartphones as well as cloud-based platforms, the coaches can be able to monitor compliance, workload, recovery and physiological reactions in real-time. This has proved especially useful during the recent COVID-19 pandemic [45] [62]. However, despite such improvements, there is still room for improvements that need to be made before these technologies can become a part of regular sporting practice. The issues related to sensor compatibility, data standardization, reliability of the devices used, cybersecurity, legal issues, as well as ethics concerning the privacy of athlete's data are among those challenges that have to be addressed. The future developments will most likely include interoperable digital ecosystems, explainable AI, federated learning, and digital twin approaches.

4. Applications in Sports Performance Evaluation

The use of wearable devices is becoming more frequent to convert the collected data from continuous physiological and biomechanical measurements into usable information for the athlete, the coach, and the sports medicine practitioner. By not constraining the use of such devices only to certain sports, wearable devices can be categorized on the basis of three fundamental objectives of performance: performance optimization, injury prevention and treatment, and customization of training and decisions [63] [64]. In terms of performance optimization, the following equipment—inertial sensors, GPS units, pressure systems, heart rate sensors, EMG sensors, and power meters—delivers data on performance technique, speed, acceleration, strength, power, and endurance. Multi-sensor systems, in particular, are helpful since they allow integrating external load parameters (distance, velocity, mechanical load) with internal reactions (heart rate, perceived exertion, and recovery of the body) [52] [64]. It enables coaches to understand if the athlete reacts to a certain training load properly, rather than just considering results.

The wearable technology devices can aid in preventing injuries and rehabilitation through assessing movement symmetry, joint loading asymmetries, fatigue-induced changes, and inadequate recovery status. In the process of rehabilitation, objective assessments of range of motion, walking, balance, muscle activation, and performance measures are vital in demonstrating the improvement and guiding the process of safe return to play [63] [65]. With the inclusion of artificial intelligence and the athlete's history profile, these measures become even more valuable for creating adaptive training programs and managing load on an individual basis. The advancement of wearable sensor technology has progressed beyond mere physiological measurement tools into smart systems that are able to offer assistance for a wide range of parameters needed for performance assessment of athletes. Being able to collect biomechanical, physiological and biochemical information on a continuous basis, such systems provide for comprehensive performance assessment, allow detecting the potential risks of injury development, and offer training recommendations for an individual athlete. The combination of wearable sensors and artificial intelligence systems makes it possible to provide real-time feedback and decision support for athletes, coaches, and specialists from the sports medicine field. **Figure 7** shows the main fields of application of wearable sensor technologies for sports performance assessment. The following subsections thus explore applications of wearables in regard to performance enhancement, injury prevention/rehabilitation, and tailored training.

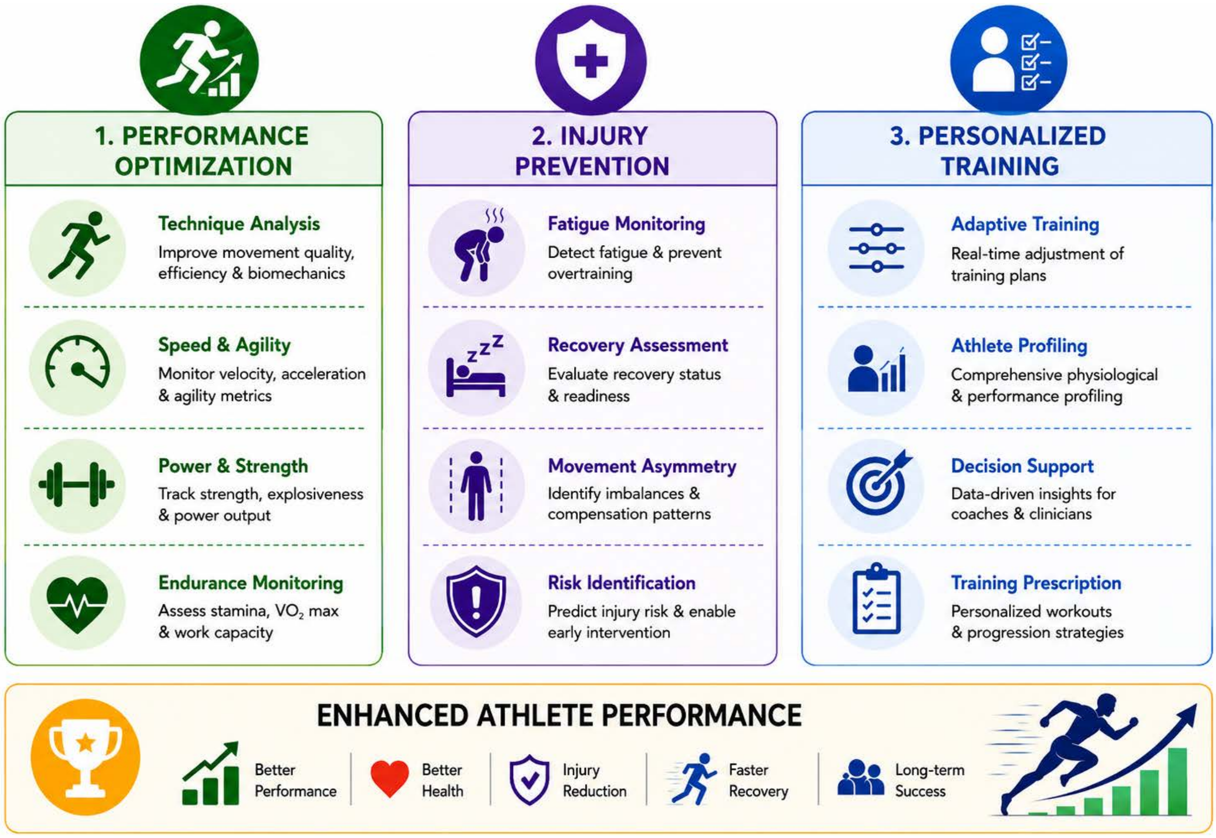

Figure 7. Major applications of wearable sensor technologies in sports performance evaluation, illustrating their roles in performance optimization, injury prevention, and personalized training to enhance athlete performance, health, and long-term development.

4.1. Performance Optimization

Optimization of athletes' performance is one of the main areas where wearable sensing technologies are applied in contemporary sports. Monitoring the biophysical, physiological, and biochemical metrics allows getting an objective set of data to optimize the technique, enhance physical performance, control the load of training and measure the level of physiological adaptation. Contrary to laboratory measurements, wearable systems allow monitoring athletes in natural training and competing conditions providing real-time feedback to conduct evidence-based coaching and personal performance enhancement [40] [63]. Biomechanical assessment of techniques is one of the oldest areas where wearable technology is employed. The inertial measurement units (IMUs), accelerometers, gyroscopes, pressure sensors, and wearable EMG systems are widely used to quantify the kinematics of the joints, body posture, limbs coordination, symmetry of movements and muscle activation. These measures help to conduct the detailed biomechanical assessment of effectiveness and precision of sports movements without using laboratory motion capture systems. Validation studies show that wearable IMU devices can measure joint kinematics within small error margins for some particular movements but the size of the error will depend on sensor locations, calibration methods, nature of the movement, the processing technique used, and the laboratory measurement system [10] [16].

Assessment of speed and acceleration is another domain where wearable technology plays a vital role. Running speed, acceleration, deceleration, sprinting distance, and change of direction performance can be measured in real time using wearable GNSS devices combined with IMUs. Modern-day 10-Hz GPS units show a significantly higher accuracy than earlier 1-Hz and 5-Hz systems when measuring total distance and high-intensity running speed and are increasingly used in elite team sports for external workload assessment [66]. Additionally, the use of GPS combined with accelerometers allows for a full measurement of exercise intensity and mechanical load. The measurement of power output has also benefited from wearable technologies. Wearable force sensors, pressure insoles, IMUs, and power meters in bikes make it possible to measure the force produced by the athlete, jump performance, pedalling economy, and biomechanics of leg muscles. Vertical jump tests have exhibited high correlations between measurements from IMUs worn on the body and measures derived from force platforms in certain validation studies [67]. High correlations are, however, highly influenced by the positioning of the sensor, jump protocol employed, filtering technique, and the statistics that are used for analysis.

In endurance testing, wearable continuously measure heart rate, heart rate variability (HRV), breathing rate, blood oxygen saturation (SpO_2), skin temperature, and external load to assess the cardiovascular and metabolic response to prolonged activity. Contemporary wearable technology allows for the individualized assessment of exercise intensity, recovery, and aerobic capacity while interfering little with training process. In combination with AI and cloud computing, longitudinal measurements by wearable technologies allow for the detection of physiological adaptation trends and evidence-based adjustments to training programs [52] [63]. Overall, wearable technologies revolutionized the performance optimization by allowing for continuous and objective monitoring of the performance metrics such as technique, speed, power, and endurance. Integration of multimodal sensors with intelligent data analysis offers comprehensive information about an athlete's performance, which allows for individualized training approach and minimizes reliance on laboratory performance testing.

4.2. Injury Prevention and Rehabilitation

Injury prevention and rehabilitation have been identified as some of the applications of wearable technologies in sports medicine through provision of constant evaluation of the quality of movements, physiology, and recovery beyond the lab or clinical environment. Contrary to traditional methods of evaluation which take place periodically, wearable offer objective and real time measures of biomechanics and physiology, hence early identification of risk factors of injuries and assessment of progress during rehabilitation [40] [63]. The most important application of wearable technology in sports medicine is identification of movement asymmetry, which occurs due to neuromuscular deficits, prior injury, and poor movement mechanics. Movement asymmetry is measured using wearable inertial measurement units (IMU), pressure insoles, EMG sensors, and force sensors for quantification of the measures of gait symmetry, joint kinematics, ground reaction forces, balance, and muscle activation. The advantage of such measures is that clinicians get the chance to spot movement abnormalities which cannot be seen through the naked eye. Recent literature shows that wearable IMUs have the ability to quantify lower limb symmetry and gait parameters with accuracy of about 5% when compared to laboratory motion analysis systems [10] [16].

Another essential approach to prevent injuries is the monitoring of fatigue since fatigue accumulates over time and changes the mechanics of movement, decreases neuromuscular control, and raises the risk of injuries. Physiological parameters such as heart rate, heart rate variability (HRV), EMG activity, running mechanics, workload, and sleep quality are constantly measured using wearable sensors to estimate fatigue in terms of both its acute and accumulated manifestations. The combination of these variables gives a better picture than the use of one single variable. The accuracy of classification models that use multiple types of data from wearable devices has reached 80% and higher [56] [58], thus showing the promise of intelligent wearable for early detection of fatigue and workload monitoring. The use of wearable devices is equally important in assessing recovery after intense physical training and musculoskeletal injuries. Measurement of the heart rate variability, heart rate at rest, time in sleep, movement, and muscle activity gives an objective measure of recovery and readiness for further physical activities. The monitoring of these variables allows the assessment of rehabilitation and determination of its correct progress. In comparison with subjective questionnaires that athletes answer themselves, physiological measurements are more objective and continuous and thus may contribute to better rehabilitation programs and avoid premature return to sports [40] [59].

With recent developments in artificial intelligence and cloud-based analysis, even greater injury prevention efforts have been made using biomechanical and physiological factors as well as training history to predict which athletes are at higher injury risk. Artificial intelligence assisted wearable are capable of picking up on subtle variations in movements, workload progression, and recovery that might happen prior to the onset of any symptoms, thus making preventative measures possible. However, according to the recent systematic reviews, the predictive value of existing injury risk models heavily depends on data quality, number of participants, external validation, and sport-specific variables, which means that at this point in time wearable technology should be seen as a supportive tool and not an independent diagnostic one [58] [65]. Overall, wearable revolutionized the processes of injury prevention and rehabilitation through objective and individualized tracking of movement asymmetry, fatigue and recovery. The combination of multimodal sensing and artificial intelligence provides important insights into optimal rehabilitation strategies, injury risks and safe return-to-play.

4.3. Personalized Training and Decision Support

The fusion of wearable with AI technology, cloud computing and digital health solutions has resulted in faster movement from generic training programs to more personalized and data-driven approaches in managing athletes. Wearable devices have made it possible to constantly monitor physiological, biomechanical and behavioural measures, and assess the responses to training individually, recovery status and performance adaptation. Personalization is critical in helping coaches and sport scientists determine optimal loads for athletes to avoid injury risks and enhance their performance through their physiological profiles [40] [55]. The primary use of wearable devices is adaptive training, where training programs are consistently altered depending on an athlete's physiological state and workload. Wearable devices track parameters such as heart rate, heart rate variability (HRV), sleep quality, efficiency of movements, external workload, and perceived exertion in order to assess readiness for training and its adaptation. This allows a more precise change of the intensity and duration of workouts and recovery period between them, thus decreasing chances of overtraining while improving performance. According to the recent systematic reviews, the combination of physiological and biomechanical data from wearable gives a more complete estimation of training readiness compared to a single parameter assessment [52] [55].

Wearable technology is also useful in creating an all-around performance profile of athletes through the continuous collection of data on physiological, biomechanical, and behavioural aspects of an athlete during training and competitive games. The advanced wearable technologies keep track of variables such as cardiovascular performance, mechanics of movements, neuromuscular activities, sleeping habits, and recovery measures in order to create personalized performance profiles. Such profiles assist in determining strengths, weaknesses, predisposition to injuries, and adaptations to training. When coupled with machine learning algorithms, athlete profiling helps predict performance trends [45] [63]. Another example of an application currently in development is tactical feedback that uses wearable to supply athletes and coaches with performance data during training and games. The devices include GPS trackers, inertial sensors, heart rate sensors, and local positioning system (LPS). They help measure the running distance, number of sprints, accelerations, decelerations, position changes, and physiological load. Using 10-Hz GPS trackers and LPS in team sports at the highest levels provides coaches with an ability to monitor the players' performance in terms of their positioning and movements with greater accuracy than previous systems, allowing the coach to assess their positioning, efficiency, and physiological load in almost real time [66].

The combination of wearable and the use of cloud-based analytics and digital health platform provide an additional benefit of personalized decision support through continuous monitoring throughout all training phases and competition periods. The analysis of longitudinal data helps to detect abnormal physiological response, reduction of performance or poor recovery, and provide timely interventions in order to prevent performance decline and possible injuries. However, the successful implementation of such approach requires high-quality data interoperability between wearable devices, transparency of algorithms used, and secure storage of athlete's sensitive data. The future development of the area is likely to include explainable AI, digital twins, and federated learning. All in all, wearable technologies have evolved the field of managing athletes to a level where training processes become customized and backed by scientific evidence. By implementing the principles of adaptive training, athlete profiling, and tactical feedback into intelligent digital environments, this approach allows for providing coaches and sports medicine practitioners with objective data.

5. Challenges and Future Perspectives

Although wearable sensors have shown tremendous advancements, there are still some challenges which make it difficult to implement such sensors in the process of sports performance analysis. Overcoming these challenges will help to increase the measurement accuracy and make wearable devices more clinically relevant as well as provide the way for further development of intelligent, personalized, and connected sensors. Firstly, it concerns the accuracy of wearable sensors during sporting activity. Despite the fact that wearable sensors showed a good correlation with lab-based measurement tools, the accuracy of measurement decreases when people perform sporting activities because of sensor displacement, soft tissue movement, and various external factors. IMU sensors, PPG sensors, and wearable EMG devices are especially prone to the motion artefact problem which makes the data received from sensors less reliable and introduces inaccuracies into heart rate, muscle activity, and kinematic measurements [4] [5] [63].

A further important constraint lies in battery longevity, especially when dealing with wearable devices used for frequent and high sensing rates and wireless transfer of data. Battery usage rises greatly when there are several sensors, GPS, Bluetooth, and AI working together at once, thereby restricting usage to just one or some days [4] [59]. Sensing rate and computational power and its trade-off with energy efficiency present an enormous engineering problem here. However, with the increasing application of cloud computing for analytics and decision-making through artificial intelligence, there is growing concern over data privacy and cyber security issues. Since the wearable devices gather sensitive physiological and health data, secure data transfer, storage, and exchange become critical. Privacy laws, like the General Data Protection Regulation (GDPR), are becoming imperative to handle data responsibly and maintain customer confidence [45]. Additionally, a lack of standard protocols for calibrating the sensors, data formats, performance parameters, and validation processes have hampered the ability of scientists and researchers to compare one wearable device from another and different studies. Thus, international standardization of testing and reporting methods should be achieved [5] [40].

However, despite the tremendous progress made in the area of wearable sensor technologies used for assessment of athletic performance, there are several scientific and technological issues preventing them from being implemented in practice on a large scale. The problems associated with sensors' reliability, comfort, battery life, data protection, and interoperability need to be resolved. On the other hand, the recent advancements in the areas of flexible electronics, energy harvesting, edge artificial intelligence, digital twins, explainable AI, and continuous biochemical sensing should help address most of these issues and create new generations of intelligent wearable devices. Figure 8 illustrates the main issues of wearable sensor technologies at present and innovations on the horizon.

Comfort and suitability for extended wear continue to be just as significant. The wearable device needs to be light, flexible, breathable, and mechanically compliant to provide minimal discomfort and not affect the performance of the signal while being worn. Uncomfortable design, skin irritation, low flexibility, and battery recharge frequency could decrease user compliance, especially during prolonged training and competitions [4] [63]. In the future, several promising technologies will change the face of sports monitoring using wearable devices. Self-powered wearable technology using triboelectric, piezoelectric, and bio fuel cell technologies allows for harnessing mechanical or biochemical energy provided by

Figure 8. Current challenges and future perspectives of wearable sensor technologies for sports performance evaluation. The figure summarizes key technological limitations together with emerging innovations expected to enable the next generation of intelligent, reliable, and personalized wearable systems.

humans' movements and eliminates the need for classic batteries [68]. At the same time, the development of flexible and stretchable electronics allows creating skin-like sensors that are mechanically durable and stable [9]. Another interesting direction is the use of artificial intelligence on the edge, when the inference from machine learning is done right on the wearable device or a smart phone nearby. The advantage of such a solution is the reduction in latency, bandwidth, and risk of privacy breach, as well as the possibility to receive real-time feedback both on training and competition. Together with the cloud computing, this solution provides hybrid processing capabilities for continuous athlete monitoring [53].

Digital twins are another paradigmatic area which starts to appear in the world of sports science. Using the data collected by wearable sensors and combining it with physiological modelling, medical history, and training data, it is possible to create continuous virtual models of athletes which will be used for prediction of their performance, planning of optimal training regimen, simulation of rehabilitation process, and assessment of risks of injuries [60]. While working in this field, more and more attention is paid to explainable artificial intelligence (XAI) to increase transparency of machine learning models [67]. Last but not least, future wearable will be able to go beyond typical physiological sensing and move on to continuous biochemical sensing. Electrochemical sensors that will be able to sense biomarkers in real time, such as lactate, glucose, cortisol, electrolytes, and pH in sweat and interstitial fluids, will allow gaining insights into athlete hydration level, metabolic adaption, stress, and fatigue. Wearable sensing in combination with physiological, biomechanical, and biochemical sensing and digital platforms powered by artificial intelligence will enable full-scale athlete monitoring and help in developing precision sports medicine [6] [9].

In summary, wearable sensing technologies are moving away from isolated monitoring devices and are becoming sophisticated integrated systems of digital health. Further developments in flexible electronics, energy harvesting, edge artificial intelligence, digital twins, explainable machine learning, and continuous biochemical sensing will help to overcome existing challenges and make wearable technologies indispensable for future evaluation of sports performance and injury prevention.

6. Conclusions

Advances in the design of wearable sensors have changed the way sports performance is evaluated because of real-time, non-invasive, and continuous monitoring of athletes both during practice and competition. Thanks to advances in microelectronics, flexible electronics, wireless communications, and artificial intelligence, wearables are no longer basic activity monitors, but intelligent devices able to record biomechanical, physiological, and biochemical parameters at once. The combination of multimodal sensors, machine learning, cloud computing, and digital health has led to an unprecedented increase in performance assessment, technique optimization, load management, injury prevention, rehabilitation, and individual athlete monitoring. However, despite such amazing advances in the field, a number of problems prevent the wide implementation of wearable in elite sports and clinical settings. The issues of accuracy due to movements and environment-related errors, as well as limited battery life, data privacy concerns, lack of interoperability, and lack of standards for validation are some of the key barriers that should be addressed in order to enable reliable long-term monitoring. Additionally, most models of artificial intelligence are trained on rather limited or sport-specific datasets, which makes the generalization quite difficult for different athletic populations.

This literature review identifies several research gaps worth noting. While significant advances have been achieved in the development of multimodal sensors, few researchers have managed to create comprehensive monitoring devices incorporating biodynamic, physiological, and biochemical measurements that can be used for long-term monitoring of athletes in the field. In addition, contemporary wearable technologies mostly provide for retrospective analysis of the athletic performance rather than for its prediction and prevention. Standardization of datasets, longitudinal research projects, interoperability of wearable ecosystems, and clinical validation of performance metrics will become crucial for implementation of research achievements in practice.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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