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Review

Advancing Sports Cardiology: Integrating Artificial Intelligence with Wearable Devices for Cardiovascular Health Management

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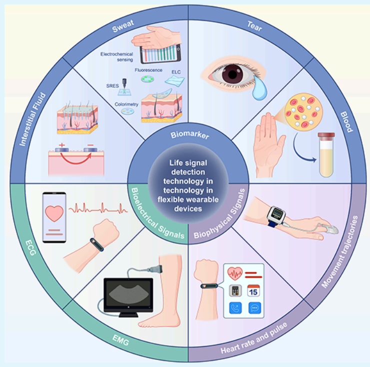
ABSTRACT: Sports cardiology focuses on athletes' cardiovascular health, yet sudden cardiac death remains a significant concern despite preventative measures. Prolonged physical activity leads to notable cardiovascular adaptations, known as the athlete's heart, which can resemble certain pathological conditions, complicating accurate diagnoses and potentially leading to serious consequences such as unnecessary exclusion from sports or missed treatment opportunities. Wearable devices, including smartwatches and smart glasses, have become prevalent for monitoring health metrics, offering potential clinical applications for sports cardiologists. These gadgets are capable of spotting exercise-induced arrhythmias, uncovering hidden heart problems, and offering crucial information for training and recovery, to minimize exercise-related cardiac incidents and enhance heart health care. However, concerns about data accuracy and the actionable value of the obtained information persist. A major challenge lies in the integration of artificial intelligence with wearables, research gaps remain regarding their ability to provide real-time, reliable, and clinically relevant insights. Combining artificial intelligence with wearable devices can improve how data is managed and used in sports cardiology. Artificial intelligence, particularly machine learning, can classify, predict, and draw inferences from the data collected by wearables, revolutionizing patient data usage. Despite artificial intelligence's proven effectiveness in managing chronic conditions, the limited research on its application in sports cardiology, particularly regarding wearables, creates a critical gap that needs to be addressed. This review examines commercially available wearables and their applications in sports cardiology, exploring how artificial intelligence can be integrated into wearable technology to advance the field.



KEYWORDS: *sports cardiology, athlete, wearable devices, artificial intelligence, cardiovascular healthcare*

1. INTRODUCTION

Sports cardiology is a growing discipline dedicated to the cardiovascular health of athletes. Even with numerous efforts to lower the occurrence of heart-related incidents in sportspeople, sudden cardiac death (SCD) continues to be a major issue.[1,2] Regular and prolonged physical activity can result in significant adaptations to the cardiovascular system. The athlete's heart is characterized by increased wall thickness and enlarged cardiac dimensions while maintaining normal systolic and diastolic functions.[3,4] Nonetheless, there is a 'gray area' where the heart's physiological changes in athletes may coincide with some medical conditions[5−9] (Figure 1). These conditions, which can mimic the adaptations seen in the athlete's heart, pose challenges in distinguishing between normal physiological changes and potentially dangerous pathology. This makes it challenging but crucial to accurately differentiate between physiological and pathological cardiac changes in athletes. For example, hypertrophic cardiomyopathy may present with similar wall thickening as the athlete's heart, but without the normal functional adaptations, potentially leading to misdiagnosis. Incorrect diagnosis can lead to significant consequences, including unwarranted disqualification from sports, misplaced confidence despite the threat of SCD, and lost chances for proper medical interventions.

Wearable technology consists of small electronic gadgets or portable computers that can wirelessly connect and are embedded in accessories, devices, or apparel, designed to be worn on the body. Intrusive types encompass microchips or intelligent tattoos. Various types of wearables have been developed, with smart glasses and smartwatches being among the most common.[10−12] The market for wearable gadgets is consistently expanding, as these devices gather, send, and interpret data from people or animals. Wearables vary from basic mechanical devices to advanced mechatronic systems, which are typically equipped with sensors, actuators, and computational components. They aid in the early detection and treatment of health issues, as well as in tracking vital signs

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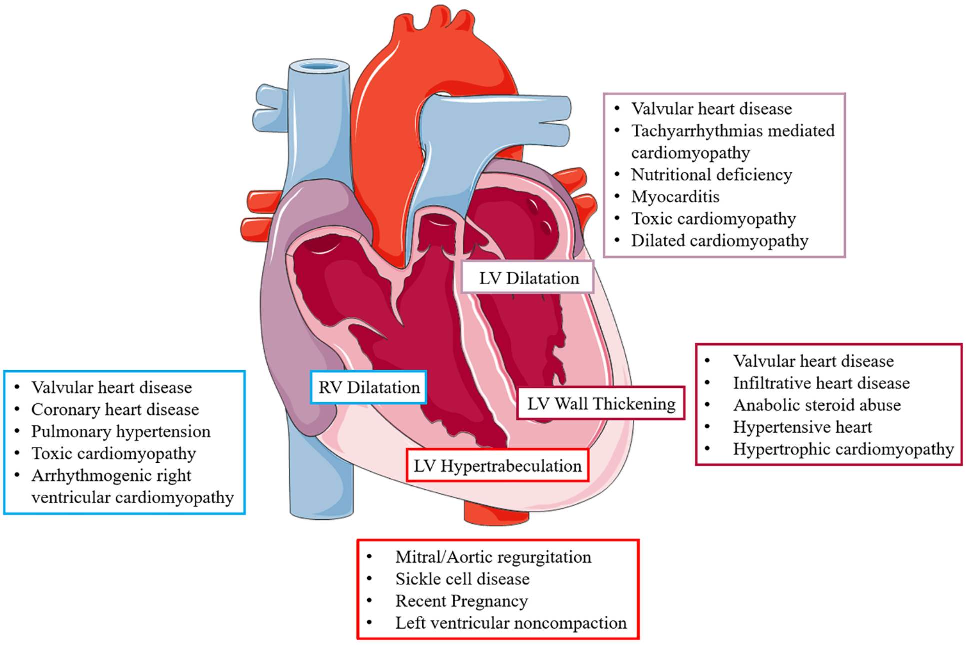

Figure 1. Differentiating between pathological and physiological cardiac adaptations to physical activity within the gray areas of athletes' hearts presents a challenge in diagnosis.

such as body and skin temperature, electroencephalogram (EEG), electrocardiogram (ECG), heart rate, and blood pressure.[13−15] These devices incorporate various technologies, capabilities, and costs, requiring users to have certain skills to operate them effectively.

Many sports enthusiasts and active individuals use devices like Apple Watches, Garmin trackers, and Polar chest straps to track health data and assess fitness and performance.[16−18] As these devices gain popularity, sports cardiologists are exploring their clinical applications, such as detecting exercise-induced arrhythmias, uncovering hidden heart problems, and offering insights on training and recovery to reduce exercise-related heart incidents and improve cardiovascular health.[19,20] However, concerns about data accuracy and the actionable value of the information remain. As sensor technologies advance and wearables become more widespread, doctors must understand their benefits and evaluate their limitations. For example, false arrhythmia alerts could cause unnecessary worry, lead to costly exams, and unjustifiably exclude people from sports. The rise of wearables has significantly impacted cardiovascular health monitoring, posing a challenge for sports cardiologists to interpret independently collected data and harness this technology for better healthcare outcomes for athletes.

The growing volume of data in healthcare requires artificial intelligence (AI) to enhance data management and utilization. AI, as defined by Russell and Norvig, involves creating smart agents that gather and process information to perform actions. In sports cardiology, AI mimics human functions, often using machine learning to analyze data. Machine learning, a subset of AI, autonomously categorizes, forecasts, and derives insights from data. These algorithms have been applied in healthcare for diagnosing and monitoring diseases, and their integration with wearable devices has the potential to transform patient data usage. Previous studies have shown AI's success in managing long-term illnesses, including heart disease, cancer, and brain disorders. The incorporation of AI in sports cardiology, especially with the growing use of wearables, shows great promise. However, few studies have explored the integration of AI and wearable devices in this field. This review examines widely used wearables and their potential applications in sports cardiology, as well as the integration of AI in wearable devices for improving sports cardiology practice.

2. BIOSIGNALS DETECTED BY WEARABLE SENSORS

Cardiovascular disease (CVD) symptoms vary by individual and condition, with common signs including arrhythmia, hypertension, coronary artery and valve damage, and stroke. According to the World Health Organization, CVDs cause over 17 million deaths annually, approximately half of the total fatalities in the United States.[21] Healthcare systems worldwide are burdened with rising treatment costs. However, wearable technology can significantly reduce these expenses by enabling remote monitoring of athletes or individuals with pre-existing heart conditions, while improving both health and performance. Wearable devices, combined with advancements in telecommunications, offer an efficient solution for continuous, nonintrusive medical tracking of athletes with heart conditions or those at risk.[22] These devices excel at real-time monitoring of cardiovascular-related bioelectrical signals, biophysical indicators, and biomarkers (Figure 2). The following sections provide a summary of the biomedical factors relevant to CVD monitoring, with Figure 3 illustrating the body parts linked to these variables.

2.1. Biochemical Signals. *2.1.1. Interstitial Fluids.* Interstitial fluid makes up about 60−70% of the body's fluids. The cells surrounding it largely determine its composition. Analyzing its composition and biophysical properties helps assess the health status of adjacent cells, aiding in cytopathology diagnosis. This fluid contains many chemicals also found in the blood, such as urea, cortisol, lactate, glucose, and cholesterol. Thus, monitoring these markers in interstitial fluid can provide insights into their levels in the blood.

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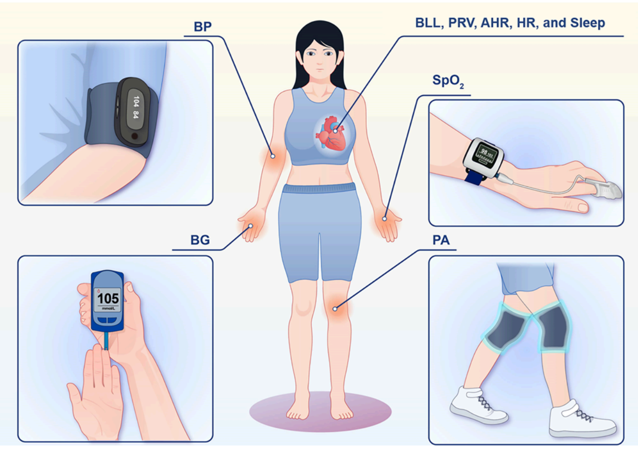

Figure 2. Body parts and their related biomedical variables. Abbreviation: BLL, Blood lipid level; PRV, Pulse rate variability; HR, Heart rate; AHR, Average heart rate; BP, Blood pressure; BG, Blood glucose; PA, Physical activity; SpO_2: Peripheral capillary oxygen saturation.

Reverse iontophoresis utilizes the potential difference between skin electrodes to extract substances. Charged ions, like sodium, migrate under an electric field toward the cathode, creating an electro-osmotic flow that induces water gradient permeation. This water movement facilitates the concurrent transport of neutral molecules, such as glucose and lactate, from the interstitial fluid to the skin surface. Paz et al. showcased a gentle skin adhesive patch that integrates a reverse iontophoretic mechanism with an amperometric lactate sensor on the anode, along with a porous hydrogel reservoir, enabling simultaneous extraction and measurement of interstitial fluid lactate through electrochemical detection (Figure 4A).[23] The device uses agarose hydrogels to prevent skin electrocution, while a poly(vinyl alcohol)-based porous hydrogel facilitates lactate movement to the biosensor. This flexible, skin-adhering patch allows lactate monitoring in resting individuals without physical exertion. For glucose monitoring via reverse iontophoresis, pH levels in interstitial fluid are critical, requiring further research. Zhu et al. designed a screen-printed glucose biosensor with reverse iontophoresis electrodes to extract interstitial fluid and monitor glucose levels[24] (Figure 4B). Their study showed that pH influences glucose extraction by altering the zeta potential, which affects iontophoretic extraction rates. These advancements in reverse iontophoresis sensors have significant implications for athlete cardiovascular health monitoring, offering continuous, noninvasive glucose and lactate data for managing energy levels and optimizing performance.

The reverse iontophoresis method typically requires 5−10 min for interstitial fluid extraction and exhibits a slow rate, which hinders real-time fluid monitoring. Advances in microneedle technology have addressed this limitation by facilitating continuous real-time detection. Teymourian et al. developed a microneedle device capable of real-time ketone

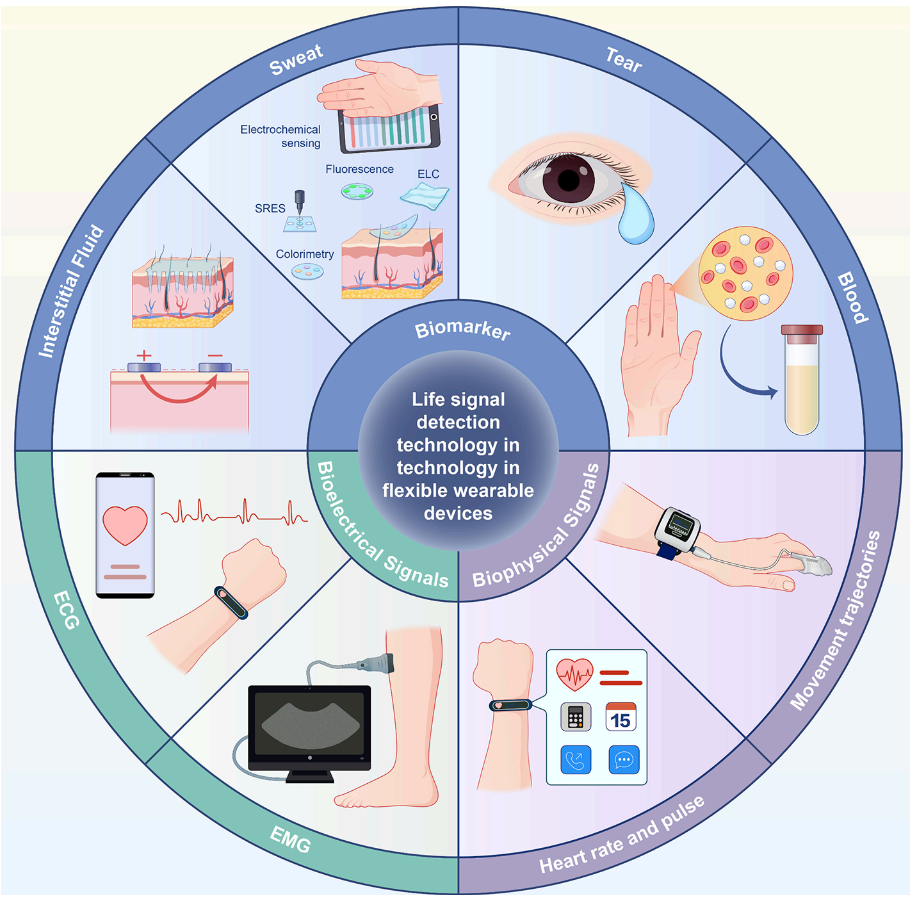

Figure 3. Categorization of vital signal monitoring by flexible wearable devices in sports cardiology. Abbreviation: ECL, electrochemiluminescence; SERS, surface-enhanced Raman scattering; ECG, electrocardiogram; EMG, electrocardiogram.

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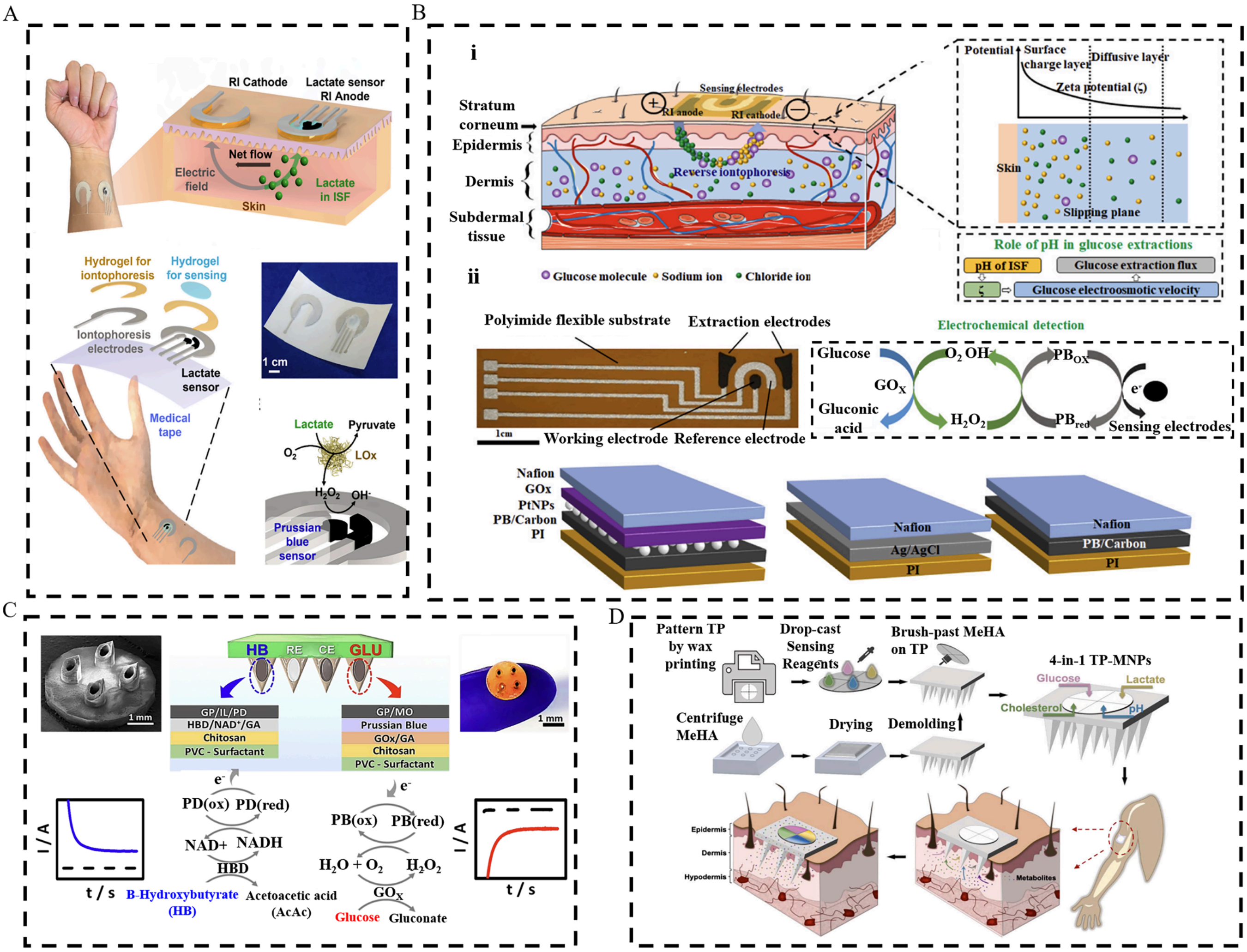

Figure 4. Interstitial fluid detection. A. Conceptual design of a noninvasive, wearable, enzyme-based patch for monitoring interstitial fluid lactate.[23] Copyright 2023 Elsevier. B. Illustration depicting glucose extraction through the skin using RI, featuring a screen-printed biosensor for electrochemical glucose detection in interstitial fluid.[24] Copyright 2023 Elsevier. C. Diagram of a dual-indicator HB/GL detection system on a microneedle sensor array.[25] Copyright 2019 American Chemical Society. D. Diagram showing the creation and use of test-paper integrated microneedle patches (TP-MNPs).[26] Copyright 2022 Elsevier.

body detection, functioning effectively within a minimal detection range (50 μm)[25] (Figure 4C). This breakthrough indicates the possibility of continuously tracking conditions like ketoacidosis and diabetic ketosis in real-time. Additionally, a new wearable epidermal system combines reverse ion introduction with an ion-conductive microneedle-based glucose sensor, significantly improving glucose extraction from interstitial fluid. This advancement is expected to support the long-term management of chronic conditions. Zhu et al. unveiled a microneedle patch composed of cross-linked methacrylated hyaluronic acid and dissolvable hyaluronic acid, aimed at quickly and painlessly extracting interstitial fluid[26] (Figure 4D). This patch, which includes wax-patterned test paper for color-based detection of metabolites such as pH, cholesterol, lactate, and glucose, allows for simple, self-conducted testing. The ability to quickly and accurately monitor these biomarkers will be valuable for home-based management of metabolic diseases and cardiovascular health in athletes.

Pu et al. leveraged ultrasound to enhance skin permeability, extracting interstitial fluid under vacuum conditions.[27] They incorporated three electrodes into a microfluidic chip, with the working electrode composed of graphite and gold nanoparticles (AuNPs) for glucose detection. This technique, referred to as sonophoresis, functions by using ultrasound to create cavities that increase skin porosity, which is further enhanced when vacuum pressure is applied. Despite generating micropores during the process, the skin remains undamaged. For athletes, this method is particularly advantageous for monitoring cardiovascular health, providing noninvasive biomarker detection to help manage energy levels and overall health.

2.1.2. Sweat. Sweat is a vital bodily fluid that contains various substances, including electrolytes, metabolites, and proteins, which can provide significant insights into an individual's health status. Common components in sweat include sodium, chloride, potassium, lactate, glucose, and C-reactive protein (CRP). These substances can be detected and monitored using a range of biochemical sensors integrated into wearable devices, providing real-time data on metabolic and physiological conditions. However, one major challenge in sweat lactate measurement is the presence of air bubbles,

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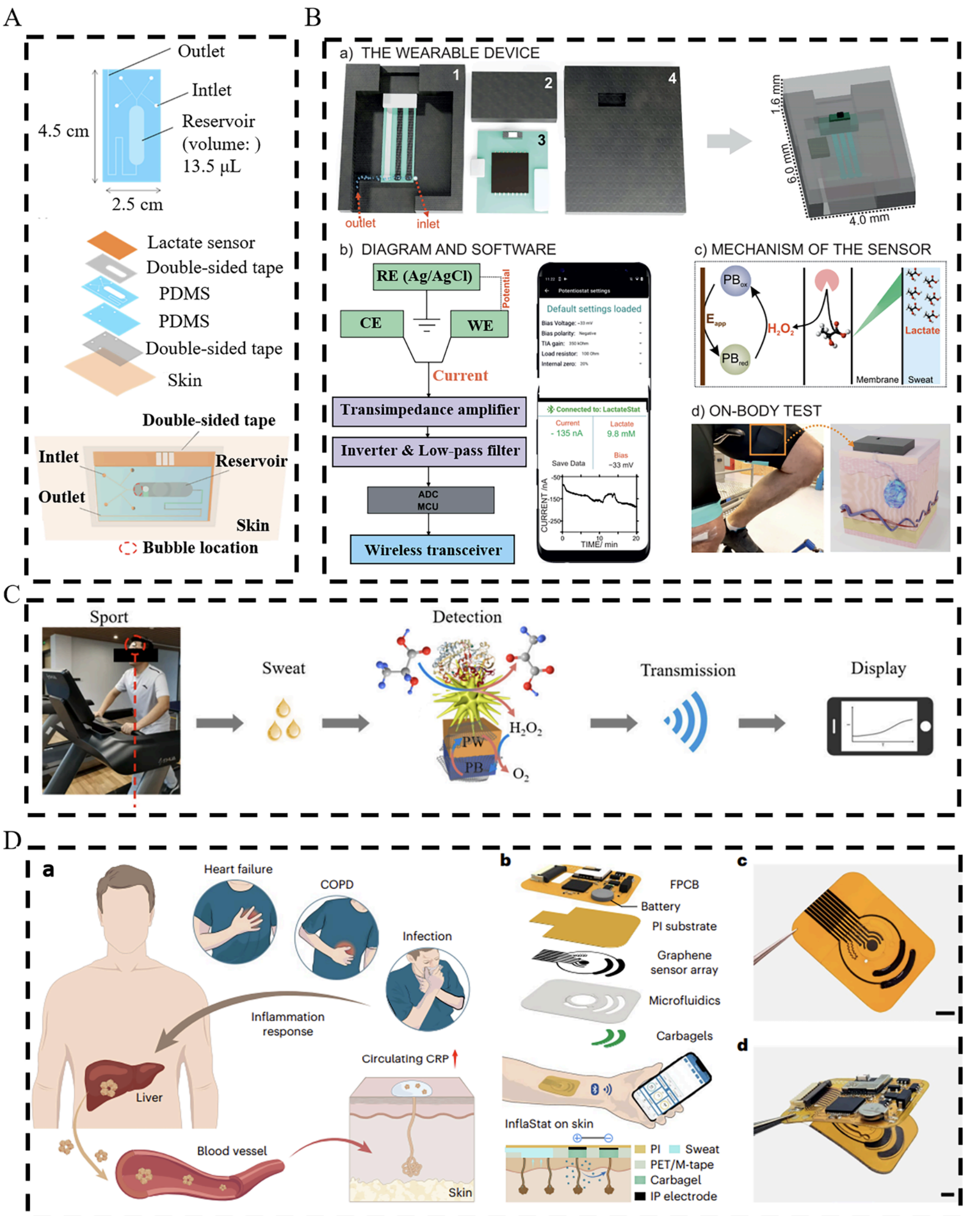

Figure 5. Sweat electrochemical detection. A. Lactate sensor and microfluidic design.[28] Copyright 2023 American Chemical Society. B. Principle behind the wearable lactic acid sensor.[29] Copyright 2023 American Chemical Society. C. Illustration of the fabricated wearable electrochemical lactate biosensor.[30] Copyright 2022 Elsevier. D. A wearable biosensor that provides automatic, wireless, and noninvasive tracking of inflammation through electrochemical methods.[31] Copyright 2023 Springer Nature.

which can disrupt the fluid flow in microfluidic sensors, causing signal inconsistencies and unreliable readings. Air bubbles form due to the variable nature of sweat secretion rates, particularly in low-sweat-rate individuals, leading to interruptions in continuous lactate monitoring. To address this issue, researchers have explored microchannel designs that facilitate the removal of trapped air, thereby enhancing measurement stability. For example, Shitanda et al. designed a lactate sensor with a microchannel to overcome the issue of air bubbles interfering with sweat lactate measurement, enabling continuous monitoring of lactate levels[28] (Figure 5A). This sensor can be worn for extended periods, making it useful in both medical and sports contexts. Additionally, a comprehensive sweat lactate monitoring system was developed for real-time perspiration analysis, confirmed by thorough on-body testing with top-tier athletes engaged in cycling and kayaking under regulated environments[29] (Figure 5B). A positive relationship was discovered among sweat lactate concentrations, blood lactate, perceived fatigue (assessed using the Borg scale), heart rate, and the respiratory quotient.

The longevity of signals in wearable electrochemical biosensors is greatly influenced by the enduring stability of functional materials on the flexible base, variations in sweat pH, and signal inconsistencies caused by sensor flexing. Jiang et al. suggested a lactate-detecting biosensor with a membrane primarily made of Prussian blue (PB), reduced graphene oxide (rGO), gold nanoparticles (AuNPs), and lactate oxidase (LOx)[30] (Figure 5C). The spin-coating technique ensured a stable PB/GO film on the electrode surface while integrating spiky gold particles and LOx-enhanced electron flow from the enzyme's active site to the electrode. This biosensor was successfully used on volunteers' skin to continuously monitor

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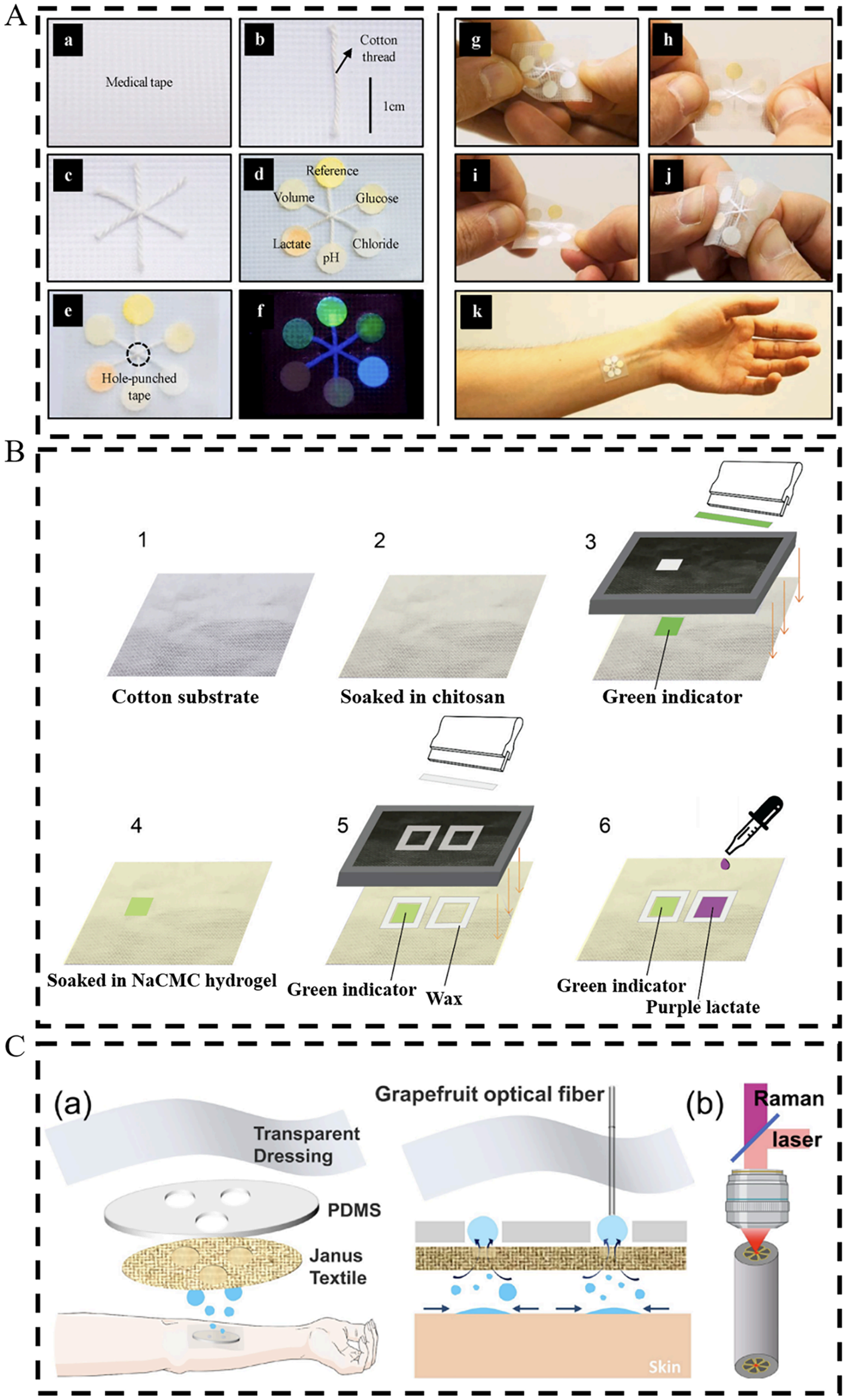

Figure 6. Sweat optical detection. A. Photographs illustrating the process of making and the mechanical adaptability of the sweat patch.[32] Copyright 2020 Elsevier. B. Diagram illustrating the design of a colorimetric sensor pattern (a) and the creation process of a textile-integrated colorimetric sensor for concurrent monitoring of sweat pH and lactate levels (b).[34] Copyright 2019 Elsevier. C. Schematic showing the method of sweat collection in Janus fabrics, laser light entering the center of the grapefruit optical fiber, and the gathering of backscattered Raman signals.[35] Copyright 2023 American Chemical Society.

sweat, yielding results similar to commercial lactate sensors. Additionally, Tu et al. created a wireless, wearable patch for real-time electrochemical monitoring of the inflammatory marker CRP in sweat[31] (Figure 5D). The device combines iontophoretic sweat collection, microfluidic pathways for analysis, and a graphene sensor array to measure CRP levels.

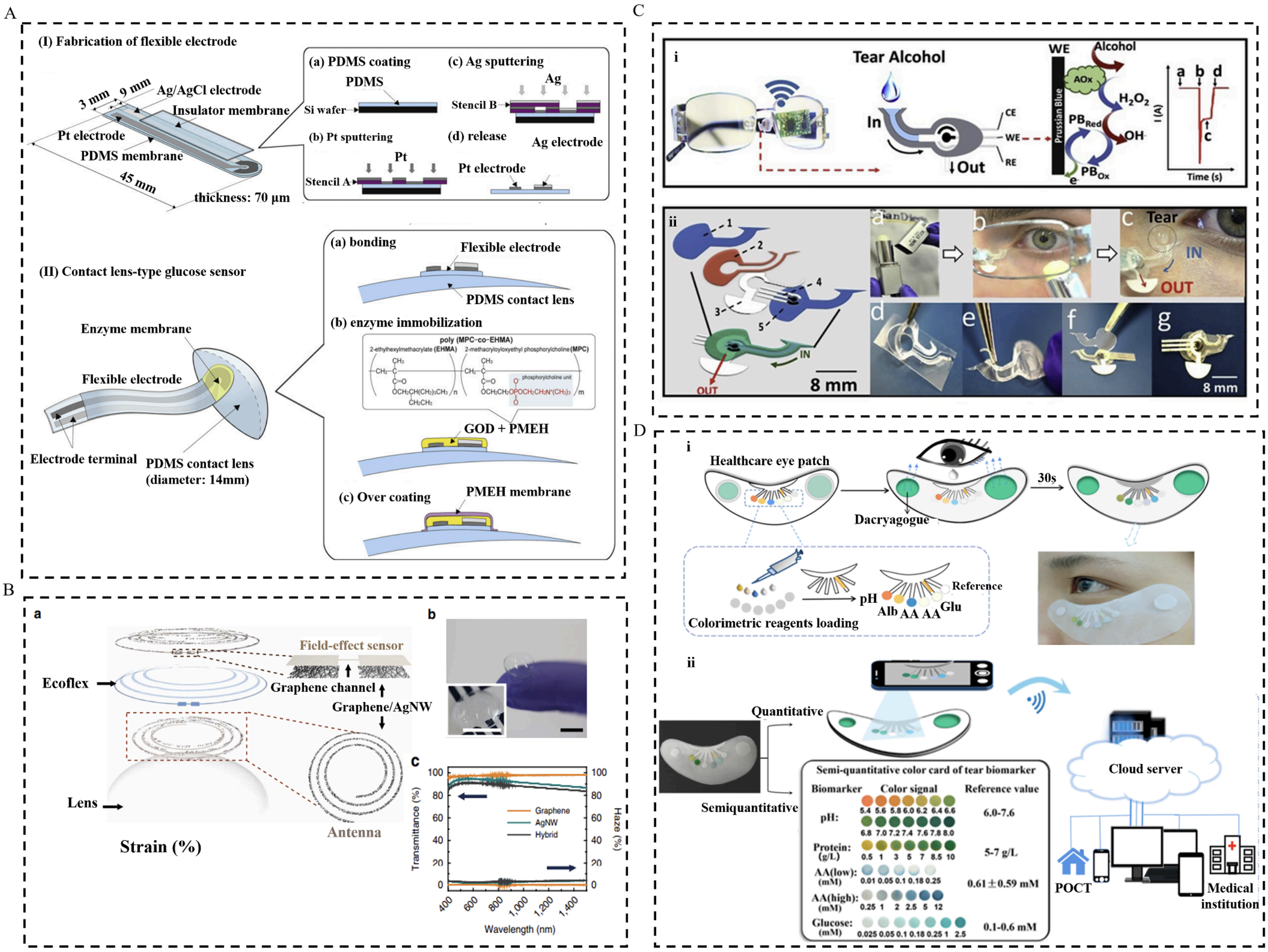

Figure 7. Tear detection. A. Procedure for creating the contact lens biosensor: (I) A 200 nm platinum working electrode and a 300 nm silver/silver chloride counter/reference electrode were deposited onto a 70 μm polydimethylsiloxane (PDMS) membrane; (II) These pliable electrodes were attached to the PDMS contact lens surface with PDMS.GOD was subsequently fixed onto the electrode's sensing area with PMEH, and ultimately, the enzyme layer was coated with PMEH.[46] Copyright 2011 Elsevier. B. Diagram of the wearable contact lens device, incorporating both a glucose monitors and an intraocular pressure gauge.[47] Copyright 2017 Springer Nature. C. (i) Images and diagrams of the fluidic apparatus embedded with wireless electronics on an eyeglasses frame, illustrating the process of enzymatic alcohol sensing and signal transmission, where (a) denotes the initial state, (b) signifies the current variation from collected tears, (c) displays the detected alcohol signal, and (d) indicates the drying phase of the device. (ii) Exploded view of the fluidic device: (1) top polycarbonate membrane, (2) double adhesive spacer, (3) paper outlet, (4) electrochemical (bio)sensor, and (5) bottom polycarbonate membrane. Tears stimulation: (a) Menthol tear stick, (b) Volunteer applying the tear stick under the left eye, (c) Tear entering the device inlet. Fluidic device construction: (d) Adhesive spacer detached from PET base, (e) Spacer positioned on the lower membrane, (f) Electrode and outlet arranged atop the spacer, followed by the upper membrane, (g) Completed device mounted on eyeglasses nose pad.[48] Copyright 2019 Elsevier. D. (i) Diagram illustrating the assay procedure with the eye patch biosensor (AA for ascorbic acid, Alb for albumin, and Glu for glucose), (ii) Evaluation through a semiquantitative card or precise measurement using a smartphone, showing wireless data transmission to a cloud service.[49] Copyright 2022 American Chemical Society.

It uses a gold nanoparticle-coated electrode with anti-CRP antibodies and monitors ionic strength, pH, and temperature for calibration. High CRP levels detected by the patch correlated with serum levels in individuals with chronic obstructive pulmonary disease, infections, or heart failure. These wearable devices for real-time inflammatory protein detection could significantly assist in managing chronic illnesses and tracking cardiovascular health in athletes.

Wearable sensors that use optical detection techniques are also used for sweat analysis, alongside electrochemical sensors. Chloride, pH, lactate, and glucose concentrations in sweat were detected using an optical wearable sensor based on cellulose[32] (Figure 6A). The device was also combined with a fluorescence imaging module on a smartphone and a custom-built app for in situ and noninvasive multisensing of sweat biomarkers. Colorimetric sensors, a common type of optical sensor for sweat analysis, offer visual detection capabilities. Zhou et al. developed a gold nanoparticle (AuNP) colloid-based sweat sensor capable of distinguishing dehydration from overhydration through color changes.[33] Fabric-based colorimetric sensors detect pH and lactic acid levels[34] (Figure 6B). The pH of sweat was evaluated with a mix of methyl orange and bromocresol green, whereas lactic acid concentrations were determined through particular enzymatic processes. Further advancements have integrated sensors into wearable fabrics, creating smart clothing with embedded sensing capabilities. Han et al. developed a wearable Janus fabric for efficient sweat collection, integrating a grapefruit optical fiber

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Table 1. Comparison of Wearable Devices for Metabolite Detection in Tear, Interstitial Fluid, and Sweat

Wearable device name	Wearable device Components	Sensing mode	Metabolite detection	Sensitivity	ref.
Epidermal iontophoretic device	The patch was developed on a medical tape with two iontophoretic electrodes, two hydrogel variants (agarose and PVA), and a LOx-based lactate sensor.	Electrochemical sensing	Lactate in interstitial fluids	The in vitro characterization of the lactate sensor showed a linear current response up to 5 mM and a limit of detection of 0.15 mM.	23
Screen-printed glucose biosensor	The patch includes a screen-printed glucose biosensor and RI extraction electrodes.	Electrochemical sensing	Glucose in interstitial fluids	The slope and linear correlation coefficient for 5 mM glucose were 0.08212 and 0.99895, respectively.	24
Continuous ketone bodies monitoring (CKM) microneedle platform	The CKM microneedle biosensor relies on an ionic liquid (IL)-based carbon paste (CP) transducer electrode incorporated with the phenanthroline dione (PD) mediator, followed by a mixed HBD/NAD+ layer, glutaraldehyde (GA) cross-linking and further coating with chitosan (Chit) and polyvinylchloride (PVC) as outer polymer layers.	Electrochemical sensing	Ketone Bodies, glucose and lactate in interstitial fluids	The CKM microneedle device displayed a low detection limit, 50 μM.	25
Test-paper incorporated microneedle patches (TP-MNPs)	The patch is made of cross-linked methacrylated hyaluronic acid (MeHA) and dissolvable hyaluronic acid (HA).	Colorimetric sensing	Glucose, lactate, cholesterol, and pH in interstitial fluids	The TP-MNPs could visually report lactic acid levels up to 3.2 mM, glucose levels up to 16 nm, cholesterol levels up to 12 mM, and pH levels in the 5−8 range.	26
Continuous glucose monitoring microsystem	The system consists of a three-electrode electrochemical sensor and a microfluidic chip.	Electrochemical sensing	Glucose in interstitial fluids	The sensor could precisely measure glucose in the linear range from 0 to 162 mg/dl with a detection limit of 1.44 mg/dl.	27
Air-Bubble-insensitive microfluidic lactate biosensor	The device integrates a lactate sensor with PDMS-based microfluidics.	Electrochemical sensing	Lactate in sweat	The sensor exhibited a concentration correlation from 1 to 50 mM and established a relationship between lactate levels in sweat and blood.	28
Fully integrated wearable device	The device consists of a disposable electrochemical lactate biosensor, a microfluidic system, an electronic board, and a userfriendly mobile application.	Electrochemical sensing	Lactate in sweat	The device displayed a low detection limit of 0.2 mM.	29
Wearable electrochemical lactate biosensor	The device consists of a PB sensing membrane incorporated with rGO and urchin-like AuNPs on flexible screen-printing carbon electrodes (SPCE)	Electrochemical sensing	Lactate in sweat	The wearable biosensor achieved a high sensitivity of 40.6 μA mM^{-1} cm^{-2} in a range of 1−222 μM and a low sensitivity of 1.9 μA mM^{-1} cm^{-2} in a wide range of 0.222−25 mM.	30
Wearable microfluidic LEG-AuNPs biosensor	The patch was created on a polyimide (PI) substrate using CO2 laser engraving and a flexible printed circuit board (FPCB) for iontophoretic sweat induction, data collection, and wireless communication. The sensor array includes an electrodeposited AuNP-decorated laser-engraved graphene (LEG) working electrode with anti-CRP capture antibodies (cAbs), a Ag/AgCl reference electrode, an LEG counter electrode for capturing and analyzing sweat CRP, an impedimetric ionic strength sensor based on LEG, a potentiometric sweat pH sensor using LEG−polyaniline, and a resistive graphene temperature sensor that is strain-insensitive.	Electrochemical sensing	CRP in sweat	The sensor showed an low detection limit of 8 pM.	31
Smart Wearable Sweat Patch (SWSP) sensor	The patch comprises highly fluorescent sensing probes embedded in paper substrates, and microfluidic channels consisted of cotton threads to harvest sweat from the skin surface and to transport it to the paper-based sensing probes.	Fluorometric sensing	Chloride, glucose, and lactate in sweat	The sensor showed low detection limits of 5 mM for chloride, 7 μM for glucose and 0.4 mM for lactate.	32
AuNP-based colorimetric sensor	The sensor consists of ascorbic-capped AuNPs.	Colorimetric sensing	NaCl in sweat	The sensor could visually report NaCl levels in the 0−47.9 mM range.	33
Noninvasive textile-based colorimetric sensor	The sensor is a cotton fabric made of chitosan, sodium carboxymethyl cellulose, indicator dye or lactate deposited on cotton	Colorimetric sensing	pH and lactate in sweat	The sensor could visually report lactate levels up to 25 mM and pH levels in the 1−14 range.	34
Wearable Janus textile-based SERS sensor	The sensor consists of a wearable Janus fabric for efficient sweat collection and a grapefruit optical fiber embedded with Ag nanoparticles as a sensitive SERS probe.	SERS sensing	Urea and lactate in sweat	The sensor showed low detection limits of 0.01 mM for urea and 0.1 mM for lactate.	35

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Table 1. continued

Wearable device name	Wearable device Components	Sensing mode	Metabolite detection	Sensitivity	ref.
Electrochemiluminescent-based lactate biosensor	The sensor utilizing electrochemiluminescence with luminol as the signaling agent was developed. Lactate oxidation was catalyzed by immobilized lactic dehydrogenase and pyruvate oxidase, using nicotinamide adenine dinucleotide as a coenzyme.	Electrochemiluminescence sensing	Lactate in sweat	The sensor showed low detection limit of 8.9×10^{-12} mol/L	36
A disposable, colorimetric, user-friendly and mass-customizable dermal patch	The patch was made up of laminated filter paper, featuring radially arranged channels or fingers with water-activated dyes positioned at their tips.	Colorimetric sensing	Sweat rate and dehydration level	The patch accommodates a wide spectrum of sweat rates and has been tested and validated against flow rates of 0.05, 0.15, 0.25, and 0.5 mL/h, corresponding to sweat intensities ranging from 1.5 to 15.3 mg/(cm^2/min).	37
Multifunctional skin-mounted microfluidic patch	The patch includes immunoassays for sweat cortisol, fluorescent assays for glucose and ascorbic acid (vitaminC), and with electrochemical sensors.	Fluorometric and electrochemical sensing	Vitamin C, cortisol, and glucose in sweat	The sensor exhibited a concentration correlation from 5 to 100 μM.	39
SwEatch	The sensor features a protective casing with a horizontally arranged system comprising various components. It includes a battery, electronics board for signal acquisition and Bluetooth wireless communication, a sealing gasket, an enclosure bottom slider, and a sweat harvester baseplate with a fluidics unit, encompassing a sweat storage reservoir and electrode locator.	Electrochemical sensing	Sodium in sweat	The device displayed a low detection limit of 17 mM.	40
Sweat collector microfluidic epidermal biosensor	The sensor comprised electrochemical sensors created through lithography and screen printing, which were integrated into a microfluidic device for real-time sweat sampling and target biomarker monitoring.	Electrochemical sensing	Lactate and glucose in sweat	The sensor showed low detection limits of 12 mM for lactate and 10 mM for glucose.	41
Soft-MEMS techniques-based wearable glucose sensor	The sensor was created by attaching glucose oxidase to a flexible hydrogen peroxide electrode. Using microelectro-mechanical systems (MEMS) techniques, the glucose sensor was produced with functional polymer membranes.	Electrochemical sensing	Glucose in tears	The sensor exhibited a concentration correlation from 0.06 to 2.00 mmol/L.	45
Soft contact lens biosensor	The sensor comprises a flexible platinum working electrode and a silver/silver chloride reference/counter electrode, fabricated using MEMS techniques.	Electrochemical sensing	Glucose in tears	The sensor exhibited a concentration correlation from 0.03 to 5.0 mM.	46
Wearable contact lens sensor	The sensor composed of a field-effect sensor and antenna on a soft contact lens.	Electrochemical sensing	Glucose in tears	The sensor exhibited a concentration correlation from 1 μM−10 mM.	47
Eyeglasses-based tear biosensing system	The microfluidic electrochemical detector was incorporated into the nose-bridge pad of eyeglasses to noninvasively monitor essential tear biomarkers.	Electrochemical sensing	Alcohol in tears	The correlation between alcohol content in tears and blood alcohol levels (BAC) is strong, with Pearson's r = 0.852, based on the electrical current values and BAC levels of the three volunteers.	48
Wearable eye patch biosensor	The sensor comprises several layers, including a textile fiber, a qualitative filter paper, the stimulation layer, and the sensing layer.	Colorimetric sensing	pH, ascorbic acid, and glucose in tears	The sensor showed low detection limits of 3 μM for lactate, 7.0 μM for glucose, and pH levels in the 5.4−8 range.	49

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embedded with silver nanoparticles as a sensitive surface-enhanced Raman scattering (SERS) probe[35] (Figure 6C). The fabric has a water-repellent inner layer and hydrophilic outer zones, enabling unidirectional sweat transport. Grapefruit optical fibers with sharp tips penetrate transparent dressings, using capillary forces to extract sweat with nanoliter-level volume requirements. Plasmonic hot spots along the fiber amplify the Raman signal of sweat components, enabling highly sensitive detection of sodium lactate and urea at subphysiological levels. This sensor facilitates real-time sweat analysis, aiding in personalized health monitoring, sports performance tracking, and cardiovascular health assessment in athletes.

Sweat analysis is essential for assessing exertion levels, optimizing training programs, and supporting cardiovascular health. Cai et al. developed an electroluminescence-based lactic acid sensor using luminol as a signaling substance.[36] The sensor quantifies lactic acid levels by detecting light emission from enzymatic hydrogen peroxide production, identifying the exertion threshold. Excessive sweating disrupts electrolyte balance, leading to dehydration. Jain et al. created a sweat rate detection patch that collects sweat chronologically and provides real-time, in situ testing.[37] A color-changing tip indicates sweat rate and dehydration levels, and the low-cost patch is suitable for mass production. Regular lactic acid monitoring helps assess the lactate threshold, optimizing training for athletes, rehab patients, seniors, and high-intensity professionals like firefighters.[38] Kim et al. developed a multifunctional sweat sensor measuring vitamin C, glucose, cortisol, and sweat rate.[39] Sweat rate is tracked via changes in electrical resistance, glucose, and vitamin C via fluorescence, and cortisol via an anticortisol antibody-AuNPs system. Near-field communication enables wireless monitoring.

Sweat is lost quickly, necessitating its storage. One common solution is incorporating sweat storage areas on sensor patches, as confirmed by McCaul et al.[40] Additionally, lithography and screen-printing techniques were employed to develop a skin-adhering microfluidic electrochemical detection system, enhancing the collection of sweat and the identification of metabolites.[41] This device features an electrode array, microfluidic pathways, sensing chambers, and medical adhesives, forming an efficient natural perspiration pump. Its design ensures stable skin contact for rapid sweat collection while eliminating initial contaminant metabolites. These advancements are crucial for athletes' cardiovascular health, offering insights into hydration and metabolic responses. However, traditional sensors may not suit individuals who sweat minimally, such as certain patients. For these cases, artificial stimulation of sweating, like pilocarpine iontophoresis (a method in which pilocarpine is delivered via electrical current to stimulate sweat production), is employed. This process works by activating muscarinic receptors on sweat glands, triggering the release of sweat through a mechanism that mimics the natural action of acetylcholine. Most current sweat sensors are limited to passive detection, with few capable of active intervention. Developing more sensors with closed-loop control functions would enhance real-time monitoring and management of athletes' cardiovascular health.

2.1.3. Tears. Tears, valued as an excellent noninvasive diagnostic fluid, are widely recognized for their effectiveness in monitoring physiological conditions due to their strong correlation with blood components.[42−44] Flexible wearable tear biosensors have become increasingly important in the field of sports medicine. The rising fascination is fueled by advancements in technology and the heightened demand for instant tracking of athletes' physical well-being, especially regarding heart health.

Flexible wearable devices crafted for tear monitoring offer significant benefits in sports settings, particularly due to their positioning around the eye, ensuring they remain lightweight and do not hinder movement. Nonetheless, applying these tear biosensors in athletic settings presents specific difficulties. The first model, a bendable strip intended to gauge glucose concentrations in tears, was developed by applying poly-dimethylsiloxane fixed onto poly(MPC-*co*-DMA).[45] Even with this advancement, keeping a secure position on the iris was challenging, reducing its practicality for daily use, especially during vigorous sports. Chu and colleagues developed a biosensor resembling a contact lens to enhance comfort and usability[46] (Figure 7A). This breakthrough entailed attaching a glucose oxidase sensor to a flexible strap, allowing for prolonged use. To improve comfort, later studies employed sophisticated materials like graphene-silver nanowire (AgNW) composites and titanium dioxide sol−gel films[47] (Figure 7B). These advancements led to the creation of biosensors similar to contact lenses, providing improved compatibility with the iris. However, direct ocular contact with these sensors raises concerns about potential eye disorders, particularly those stemming from heat generated by wireless transmission modules. To mitigate these hazards, Sempionatto and his team developed a frame-mounted wearable sensor for tears[48] (Figure 7C). This novel design demonstrated the feasibility of detecting extraocular tears for the first time. This sensor, designed to gather tears from the eye's edge, can identify both alcohol and external tears through a bioenzyme−substrate reaction, without touching the eye directly. In addition, Xu et al. designed an innovative noninvasive wearable biosensor capable of simultaneously analyzing multiple crucial biomarkers in human tears[49] (Figure 7D). This sensor, uniquely fashioned as an easy-to-use eye patch, comfortably fits beneath the eyes. Different regions on the eye patch are coated with particular color-changing chemicals to specifically identify glucose, vitamin C, proteins, and pH levels in tears. The examination needs only one teardrop (approximately 20 μL) and provides outcomes in under half a minute.

We evaluated devices for monitoring tears, interstitial fluid, and sweat, comparing tear detection products with those designed for sweat and interstitial fluid (Table 1), and discovered that advancements in sensor technology have mainly boosted the sensitivity of existing products. Most monitoring limitations arise from changes in biomarker composition. Despite significant advancements in enhancing sensor comfort, safety, and effectiveness, especially during physical activities, their susceptibility remains a subject for further investigation.

2.1.4. Blood. Blood holds numerous health-related substances. In medical practice, blood tests are considered a gold standard for diagnosing health conditions. Typically, these tests involve invasive methods, such as drawing a blood sample. However, recently developed devices enable noninvasive testing. These devices primarily measure blood pressure, blood glucose, and blood oxygen levels.

Pulse oximetry, a widely utilized commercial blood oxygen testing device, necessitates precise mounting and usage. Nonetheless, its substantial dimensions and significant energy usage limit its use for real-time, remote surveillance.[50]

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Plethysmography (PPG)--based sensors, consisting of light-emitting diodes and photodetectors (PD), facilitate blood oxygen detection in opaque tissues.[51] These devices can detect transmitted or reflected light from tissues, which is then converted into electrical signals. Flexible organic photodetectors (OPD) provide superior skin conformity and comfort compared to stiff PPG sensors. For instance, Bae et al. created a hybrid gadget integrating micro-LEDs, organic photodetectors, and heaters embedded in polydimethylsiloxane (PDMS), demonstrating robust emissions and 50% stretchability, employed to track vital signs like heart rate, deep breathing, coughing, and blood oxygen levels.[52] Kim et al. combined flexible electronics with near-field communication to create an ultracompact, wearable earlobe sensor for continuous blood oxygen monitoring for up to three months, though motion artifacts remain a challenge.[53] To address miniaturization, Abdollahi et al. used free-form 3D printing to design personalized pulse oximeters with red/infrared LEDs, pressure sensors, and flexible circuits, achieving accuracy at rest but facing issues during movement due to pressure-induced contact variations.[54] A wearable ambient light oximeter (ALO) that uses various ambient light sources eliminates the need for LEDs.[55] By integrating spectral filters and optical path differences, this apparatus gauged blood oxygen levels on the index finger across various lighting environments, matching the reliability of commercial pulse oximeters.[55] These advancements in noninvasive monitoring technologies are particularly relevant for athletes, as they provide continuous and accurate blood oxygen levels crucial for cardiovascular health and performance optimization during training and competition.

Blood glucose is a key health indicator, but traditional testing methods are invasive, relying on electrochemical detection. Noninvasive optical sensing, using PPG sensors with near-infrared (NIR) and Raman spectroscopy, provides a more comfortable alternative. Yang et al. developed a NIR serum glucose monitoring device combining photoacoustic spectroscopy with machine learning algorithms.[56] This system uses a continuous-wave laser (1500−1630 nm) to excite glucose in aqueous solutions, with deep neural networks enhancing accuracy compared to other NIR methods. For other biomarkers like blood lactate, innovative noninvasive sensors are emerging. Mason et al. created a microwave-range electromagnetic lactate sensor that correlates well with invasive testing (R^2 = 0.78, 13.4% error within 0−12 mmol/L).[57] Moreover, NIR-based devices such as the BSX Insight can track blood lactate levels during workouts to estimate the lactate threshold.[57] These advancements in noninvasive monitoring are particularly beneficial for athletes. Continuous and accurate measurement of blood glucose and lactate levels is crucial for optimizing training regimes and ensuring cardiovascular health, as these biomarkers directly influence energy metabolism and performance.

2.2. Biophysical Signals. *2.2.1. Paths of Movement.* In athletic contexts, the accelerometer is a crucial device utilized in numerous areas, including practice, competitive events, wellness tracking, and recreational activities. By accurately measuring acceleration and trajectory, it offers athletes and regular users an enhanced, individualized sports experience, contributing to better cardiovascular health monitoring and performance optimization.

Flexible wearable devices use accelerometers and various sensing mechanisms—capacitance, piezoresistivity, triboelectricity, and piezoelectricity—to monitor movement and cardiovascular health. These sensors offer high sensitivity, durability, and flexibility. Wang et al. developed self-sticking strain sensors with a water-based polyurethane adhesive to track neck, wrist, and ankle movements, enhancing sensitivity and minimizing motion interference.[58] Bi et al. improved upon this by integrating conductive textiles with rGO/carbonate ink/PVA, enabling posture correction for elite athletes.[59] Zhao et al. advanced the field further with a transparent, flexible ionic skin system that detects hand gestures and transmits them wirelessly for sign language interpretation.[60] Additionally, some researchers have specifically designed accelerometers for foot movement. For example, Mao and colleagues created an intelligent sock incorporating a TENG, signal processing circuits, and a microcontroller equipped with a wireless transmitter.[61] This sock efficiently tracks foot pressure and employs neural network algorithms to assess and observe walking patterns and balance, which is essential for athletes' heart health and performance enhancement.[61,62]

In summary, wearable sensor technology has evolved from simple tracking mechanisms to sophisticated systems with enhanced sensitivity, supporting applications in sports training and motion analysis. With continued advancements in AI, flexible wearables equipped with accelerometers and advanced algorithms offer intelligent monitoring solutions, overcoming challenges like movement artifacts and perspiration, particularly in tracking cardiovascular health in athletes.

2.2.2. Heart Rate and Pulse. In order to achieve precise and sensitive monitoring of cardiovascular health with minimal interference from body movements, advancements in flexible devices have combined electrical, pressure, and optical sensing technologies. These techniques allow for gathering heart rate and pulse data from locations such as the fingers, neck, chest, and wrist.

Flexible gadgets now enable real-time, remote tracking of heart rate, breathing, and electrocardiograms, essential for athletes' heart health. These devices use electrical sensing methods like peak detection and ECG signal averaging, supported by hybrid electronic systems.[63−65] Pressure sensors, such as those developed by Rasheed et al., use piezoelectric designs and amorphous silicon bigate TFTs for multipoint heart rate monitoring.[66] Chen et al. created flexible piezoresistive sensors for pulse detection,[67] offering highly sensitive tracking with minimal resistance and greater comfort. A more user-friendly approach for monitoring employs photoelectric PPG to detect blood flow volume changes through the skin, thereby extracting heart rate data. Scardulla et al. analyzed the interaction of contact pressure between the PPG sensor and the skin.[68] Building on this, Wang et al. developed a PI interface sensor that integrates a platinum film thermistor with a reflective PPG sensor to gauge the contact pressure between the sensor and the skin.[69] Advancements in PPG technology have resulted in more efficient sensor designs, guaranteeing that flexible wearable devices retain their pliability, comfort, softness, and mechanical compatibility, which are crucial for extended use, particularly in sports settings. Overall, the evolution of heart rate and pulse monitoring in flexible wearables has moved from simple electrical detection to advanced pressure and optical sensing, enhancing sensitivity and accuracy. These developments ensure reliable cardiovascular health monitoring for athletes during physical activities.

2.3. Bioelectrical Signals. *2.3.1. Heart Function.* Traditional ECG machines, which use wet electrodes, provide

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accurate heart activity readings but are designed for short, stationary assessments. Their complexity and size make them unsuitable for dynamic environments like sports, where continuous cardiovascular monitoring is crucial. To address this, Kim et al. developed a flexible wearable ECG device using thin-film electronics and ultraelastic elastomers, allowing for continuous data collection during physical activities.[70] This design optimizes accuracy while minimizing user disruption. Expanding on this, Li et al. have advanced the precision of exercise state detection in wearable technology by enhancing denoising methods for ECG and EMG signals.[71] Their method combines an enhanced Variational Mode Decomposition (VMD) with the Improved Sparrow Search Algorithm and Second-Generation Wavelet Transform (ISSA-VMD-SWT), using chaos mapping to improve the algorithm's initial population. This technique effectively minimizes noise while retaining critical fatigue-related indicators. Testing with data from 32 individuals revealed accuracy levels of 93.05%, 95.16%, and 93.25% for classifying "Tired", "Transition," and "Easy" exercise states, respectively, demonstrating substantial improvements over traditional denoising methods. Furthermore, Li and Yang et al. focused on detecting minute heart rate fluctuations, with their efforts aimed at overcoming the challenges of skin resistance and perspiration accumulation during exercise, resulting in degradation of the interfacial conformality and adhesion, causing signal artifacts and unstable biopotential measurements.[72,73] These advancements have led to more compact and user-friendly ECG monitors for sports, progressively reducing external interference and enhancing their suitability for the active demands of athletic environments.

3. TYPES AND CAPABILITIES OF WEARABLES

3.1. Movement Sensors. Wearable devices use motion sensors like biaxial or triaxial accelerometers to capture activity parameters such as walking, running, and cycling. These accelerometers are often combined with. Global positioning satellite (GPS) for spatial positioning, barometers to detect altitude changes, and gyroscopes to measure angular motion, offering valuable insights for sports cardiology. Pedometers are a fundamental type of motion sensor, measuring steps when vertical acceleration exceeds a set threshold. Although limited in competitive environments, pedometers are useful for tracking daily physical activity, and promoting cardiovascular health in athletes.[74,75] Accelerometers and gyroscopes, integrated with microchips, are key in analyzing athletic performance and optimizing exercise regimes. MEMS technology enables compact, multidimensional sensors that estimate energy expenditure and assess training intensity. These devices are widely used in consumer products like FitBit and Jawbone Up, providing real-time data on heart rate, calorie burn, and performance across various sports.[76−78] In Australian football, accelerometer data highlight positional differences in physical demands across various levels of competition,[79] offering insights crucial for cardiovascular health management in athletes. GPS devices offer an alternative to accelerometers for tracking positional data in sports and exercise physiology. GPS technology has been extensively utilized in sports like football, orienteering, cross-country skiing, and field hockey to monitor athlete speed and position. In elite sports like Australian football and rugby, GPS-enabled gadgets such as Garmin's Vivofit and Vivoactive, Polar's M400, and FitBit's Surge offer live data on various metrics including distance, steps, pace, calories burned, altitude, and speed.[80,81] These devices also facilitate performance tracking through software programs. This capability is particularly valuable for monitoring cardiovascular health and ensuring athletes are training within safe parameters. However, the applicability of GPS in court-based sports with shorter distances and higher intensities remains an area requiring further validation. Additionally, force sensors, including force-sensitive resistors and load cells, measure applied forces.[82,83] These sensors are crucial in understanding movement dynamics, balance, and muscle performance. Force-sensitive resistors are often used in footwear insoles to assess foot pressure, while in the upper limbs, they measure muscle contractions.[84,85] These sensors are integral to monitoring cardiovascular health, enhancing performance, and preventing injuries in athletes.

3.2. Physiologic Sensors. Currently available wearables monitor various physiological measurements, including skin temperature, peripheral capillary oxygen saturation (SpO_2), respiratory rate, heart rate variability, and heart rate. Advanced devices can also estimate maximal oxygen uptake (VO_2 max), which assesses aerobic capacity, offering valuable insights into cardiovascular health and exercise performance.

Most wearables utilize PPG technology to measure SpO_2 and heart rate, employing optical techniques to assess changes in blood volume within microvessels.[86] By emitting light (e.g., 365 nm wavelength LED) onto the capillary bed, PPG measures the light intensity either transmitted through or reflected from the tissue, detected by a photodiode.[87] In resting conditions, commercial wearables show comparable performance to traditional clinical vital signs monitors across a broad heart rate range.[88] During aerobic exercise, these wearables generally correlate well with standard ECG monitoring.[89] Chest strap monitors, such as the Polar H7, show the greatest consistency with ECG readings (r = 0.99) among different groups, while wrist-worn heart rate monitors that use optical technology display varying levels of accuracy depending on the model (r = 0.52−0.92).[90,91] Notably, wrist-worn devices perform less reliably during activities like elliptical training with arm levers ($r < 0.80$).[92] In comparison, the Apple Watch Series III exhibits a high correlation with ECG readings during treadmill use (r = 0.96), whereas other devices such as the Fitbit Iconic, Garmin Vivosmart heart rate, and TomTom Spark 3 show a marginally lower correlation (r = 0.89).[93] The precision of wrist-worn monitors can be influenced by elements like skin tone, hydration levels, and body art.[94,95] For example, darker skin tones (and tattoos), which absorb greener light due to melanin, can reduce light reflection and impact signal accuracy.[94] Additionally, hydration levels, which affect skin resistance, can also influence the performance of wrist-worn monitors, as skin resistance decreases with increasing hydration.[96] Overall, given the inconsistent accuracy of wrist-worn devices, it is recommended to exercise caution when analyzing their data. For more accurate heart rate monitoring during physical activity, chest strap monitors are suggested, especially for clinical or performance-related purposes.

With recent progress, smartwatches now include direct ECG electrode recording to monitor heart rate and rhythm.[97] Gadgets such as the Apple Watch and Fitbit Sense employ electrodes located on the sides and back of the device to record a rhythm strip similar to lead I. Users can initiate a single-lead ECG by touching the digital crown with a finger from the opposite hand. By moving the watch to the ankle and

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Table 2. Mechanisms, Applications, and Constraints of Wearable Devices[a]

	BCG	PPG	ECG
Mechanisms	Measure the body's motion caused by the abrupt expulsion of blood with every heartbeat.	Identify variations in microvascular blood volume.	Assess the heart's electrical activity using electrodes placed on the skin's surface.
Applications	Beneficial for monitoring essential physiological signs.	Sufficient for detecting heart rate.	The benchmark for measuring heart rate and variability.
Constraints	The accuracy can be influenced by the placement on the body and is dependent on the individual's posture, such as whether they are sitting or lying down.	In cases of arrhythmias with reduced pulse generation, such as atrial fibrillation, heart rate may be underestimated.	The quality of the signal is influenced by the electrode-skin contact.

[a]BCG, Ballistocardiograms; PPG, Photoplethysmography sensors; ECG, electrocardiogram.

positioning either hand on the crown, additional techniques allow for the capture of leads II and III. Device adjustments can also be used to acquire precordial leads. This feature allows for continuous PPG heart rhythm monitoring with the flexibility to perform single-lead ECG monitoring as required, enhancing monitoring capabilities in both clinical and personal fitness settings.[98,99]

4. BENEFITS OF WEARABLE TECHNOLOGY IN SPORTS CARDIOLOGY

Sports teams constantly seek ways to enhance athlete performance and safety to gain a competitive edge. In the last ten years, techniques like video capture and digital computer analysis have been utilized to track human motion and enhance athletic performance.[100−102] Although these methods were once advanced, they faced challenges such as questionable data validity, labor-intensive data collection, manual notation, and an inability to track vital metrics like biosignals, physiological parameters, and biochemical data, which are crucial for real-time health and performance insights. Recent developments in wearable sensor technology have provided new opportunities to address these issues and are now being adopted by teams worldwide. Table 2 outlines the different available technologies in the field of wearable device-driven sports cardiology.

One significant challenge in the wearables field is translating data into actionable insights within its clinical domain. Inquiries such as 'how should the data be utilized' or 'what is the significance of the data' have obstructed the efficient application of this technology. To overcome these obstacles, sports teams have started hiring "sports scientists" whose roles include translating sensor data into comprehensible metrics for coaches, trainers, players, and other stakeholders. These sports scientists utilize various frameworks such as the "Performance Profiling Methodology" and "Data-driven Decision-Making Models" to ensure that the data gathered from wearables is analyzed accurately and converted into actionable strategies. For instance, the "Performance Profiling Methodology" allows coaches to create individual performance profiles for each athlete, incorporating data from wearables to identify strengths and weaknesses, while data-driven models offer predictive analytics to adjust training regimens in real-time. This integration aims to enhance rehabilitation therapies and improve athlete health and performance. For instance, wearable device data on player movement can inform coaches about workout loads, identifying athletes at higher risk for soft-tissue injuries or those needing rest during intense training periods.[103,104] One National Football League (NFL) coach highlighted that using such technology, combined with insightful analytics and tailored recovery protocols, significantly reduced soft-tissue injuries over two years.[105]

Monitoring an athlete's position and movement is critical for developing improved training regimens to maximize individual performance. The accuracy of devices like pedometers has been questioned and recently studied. Scientists evaluated the precision of step-counting capabilities in smartphone pedometer applications (Galaxy S4Moves App, iPhone 5s Moves App, iPhone 5s Health Mate App, iPhone 5s Fitbit App) and wearable gadgets (Nike Fuelband, Jawbone UP24, Fitbit Flex, Fitbit One, Fitbit Zip, and Digi-Walker SW-200) by comparing them to direct step count observations.[106] The findings indicated a relative variance in the mean step counts between actual and reported data: −0.3% to 1.0% for pedometers and accelerometers, −22.7% to −1.5% for wearables, and −6.7% to 6.2% for smartphone apps. These variations were credited to the strength of integrated circuit technology and the software algorithms employed to identify a step.[106] Accurate step counts are essential for calculating other physical activity metrics like distance covered or calories burned, which is vital for customizing training programs for top-tier athletes.

Wearable sensors in athletics are still in their infancy, with the majority of gadgets now tracking movement-related metrics such as distance, speed, and acceleration. A substantial necessity persists to 'measure the athlete' through the assessment of biochemical indicators like electrolytes, analytes, and neuropeptides, which reflect physical effort, fitness levels, exhaustion, and cognitive sharpness. Integrating these advanced measurements into sports cardiology and performance analysis could revolutionize athlete training and health management.

4.1. Wearables to Screen for Cardiovascular Disease in Athletes. With advancements in sensor technology and algorithm development, wearables are now evolving to not only track athletic performance but also detect potential health issues, particularly cardiovascular concerns. Wearable devices in sports cardiology could play a crucial role in evaluating and preventing SCD in athletes. High-intensity physical activity can induce ventricular arrhythmias in individuals with hidden cardiac conditions linked to SCD. Although the precise rate of SCD in athletes varies by factors such as age, gender, and type of sport, it is noted to be as high as 1 in 15,000 among young male soccer players.[107,108] In the future, it is possible that wearables could aid in identifying previously undetected exercise-induced arrhythmias in athletes with cardiovascular issues. With advancements in algorithm development, wearables might eventually predict health events automatically, pinpointing at-risk athletes who might otherwise be missed by standard screening processes. These technological strides could enable the early detection of conditions tied to SCD, potentially allowing for interventions that reduce SCD risk in affected athletes. In the context of sports performance, wearable technology can monitor vital signs and physiological

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responses during training and competition. This data can be used to optimize training programs, enhance performance, and ensure athlete safety. Wearable devices offer immediate information about an athlete's heart health, aiding in the prevention of negative incidents and enhancing overall performance.

Long QT syndrome is a heart rhythm disorder, characterized by prolonged QT intervals on an ECG, which increases the risk of arrhythmias. It is a major factor contributing to SCD in young sports players. Some research indicates that the Apple Watch Series 4 can accurately measure QT intervals in 85% of patients with normal heart rhythm by using ECG equivalents of leads I, II, and V6. The primary limitations are the quality of ECG tracings and T-wave amplitude.[109] Despite its promising potential, the clinical application of wearable ECG devices such as the Apple Watch for diagnosing Long QT syndrome is still hindered by several factors. First, these devices may not always provide accurate readings due to factors such as movement artifacts, poor electrode contact, and the limited number of leads used, which may miss subtle abnormalities. Additionally, the interpretation of ECG data from wearables requires expertise, and it is challenging to ensure consistency across different users and environments. In clinical practice, these devices may need to be used alongside traditional ECGs or other diagnostic tests for confirmation, particularly in the case of at-risk populations. While systematic preparticipation screening (PPS), including ECG, has proven effective in identifying young athletes with potentially lethal cardiovascular abnormalities and protecting them from sport-related SCD, the practicality of identifying Long QT syndrome through wearable technology is still uncertain.[110] Nonetheless, it is conceivable that such devices could eventually be used for screening a large number of young people for this condition.

At present, it is impractical to reliably use wearable devices to detect other conditions linked to SCD in athletes. Nonetheless, growing data suggests that wearable devices are capable of detecting irregular heart rhythms, including atrial fibrillation. The Apple Heart Study, involving 419,297 individuals over eight months, discovered that a PPG algorithm identified irregular heartbeats in 0.52% of the participants.[111] Interestingly, just 0.16% of individuals between 22 and 40 were notified, whereas 3.1% of people aged 65 and above received alerts. Among those who received irregular pulse alerts and wore an ECG patch at the same time, the positive predictive value (PPV) for detecting an irregular pulse was 84%. Similarly, the Huawei Heart Study, which monitored pulse rhythms in 187,912 participants, reported that 424 received notifications for suspected atrial fibrillation. Of those who sought medical evaluation, the PPV was 87%,[112] aligning with the Apple Heart Study findings. Considering that atrial fibrillation occurs more frequently among male master's endurance athletes compared to the general population, the PPV could be elevated in this particular demographic.[113]

4.2. Wearable Devices for Exercise Guidance.

4.2.1. Training Based on Heart Rate Zones. Wearables enable individuals to use heart rate to regulate training intensity. This method can assist in designing athlete training plans and tailoring exercise routines for cardiac patients. Stamina workouts frequently involve extended aerobic activities at levels where lactate balance is maintained, referred to as Zone 2, in addition to high-intensity interval training (HIIT), characterized by short, vigorous bursts.[114] The most accurate way to determine specific training intensities for many is through a cardiopulmonary exercise test. After identifying these intensities, the associated heart rate can serve as a guide for future workouts. For individuals without access to this test, heart rate zone training and HIIT can be estimated by using percentages of their predicted maximum heart rate.

Furthermore, providing secure workout recommendations for athletes with coronary artery disease or conditions associated with sudden cardiac death is an essential and developing area in sports cardiology. Although the American Heart Association and the American College of Cardiology typically advise athletes to engage in low-intensity (Class IA) sports for numerous conditions,[115] recent revisions suggest a more adaptable stance, particularly when the effects of exercise on disease progression or sudden cardiac death risk are unclear.[116] Consequently, wearable devices can offer immediate, unbiased feedback during workouts, potentially aiding in maintaining the recommended training levels. Any wearable technology strategy for athletes with diagnosed cardiovascular conditions must be thoroughly validated for device precision and medical safety via clinical studies. The growing enthusiasm for home-centered cardiac rehab for individuals with heart conditions could further confirm the precision, safety, and efficacy of wearable devices in this group.[117]

As previously noted, wrist-worn heart rate monitors exhibit varying accuracy, particularly during exercises involving extensive arm movements. Consequently, when guiding athletes on training regimens that rely on heart rate or recommending exercise for those with heart issues, it is essential to acknowledge the inaccuracies of wearable devices. Optimal guidance is expected from using a chest strap monitor rather than wrist-worn devices.

4.2.2. Heart Rate Variability-Guided Training. Wearable devices offer more than just heart rate metrics; they also provide objective data on internal workload and recovery. External workload denotes the physical effort an athlete puts forth, often quantified by biomechanical actions like speed and acceleration. In contrast, internal workload captures the body's physiological response to this external load. This is often assessed using wellness questionnaires that evaluate an athlete's response to previous workouts and recent stress, recovery, and sleep levels. Internal workload encompasses subjective assessments during physical activity, such as perceived exertion ratings using scales like those developed by Borg or Foster.[118,119] Sports scientists use RPE along with the length of the training session to measure an athlete's internal workload for a particular exercise. Coaches and trainers can use these metrics to ensure adequate recovery between training sessions. Proper recovery is crucial in competitive sports to prevent injuries and avoid training plateaus. Overreaching or overtraining can occur when there is an imbalance between training load and recovery.[120]

Considering the personal nature of wellness surveys and perceived exertion ratings, data from wearable devices can enhance these evaluations to better gauge athletes' internal workload levels. Wearable devices are progressively utilizing deviations in skin temperature and breathing rate from normal daily rhythms, along with heart rate variability data, as objective indicators of internal strain and recuperation. Heart rate variability, which indicates changes in the autonomic nervous system, offers a thorough evaluation of exercise, rest, diet, and mental as well as emotional stress. Lundstrom et al. explored if daily monitoring of heart rate variability could improve endurance training outcomes more effectively than a

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fixed training regimen in healthy, moderately fit male athletes.[121] Heart rate variability was measured every morning using a Polar S810i monitor. The training intensity was modified according to heart rate variability; a drop in heart rate variability resulted in lower intensity, whereas stable or increased heart rate variability permitted higher intensity.[122] The guidelines permitted up to two back-to-back high-intensity or rest days, requiring a rest day after nine straight days of training, irrespective of heart rate variability. Although both groups trained six times a week, athletes using heart rate variability to guide their training, with only three high-intensity sessions compared to four in the standard program, experienced notably better gains in maximum running speed and a larger, albeit not statistically significant, rise in VO2peak.[123] Analogous research involving both genders revealed steady outcomes in men, whereas women in the heart rate variability-guided cohort attained equivalent cardiovascular performance enhancements with reduced training intensity.[124] Later studies back these results, showing improved sports performance through training guided by heart rate variability. However, wearables encounter challenges in accurately measuring heart rate variability. Certain research employs a 7-day moving average of the root-mean-square of successive differences (RMSSD) between normal heartbeats, as it is more responsive to variations in training status compared to single-day measurements.[125] Despite challenges in obtaining accurate heart rate variability data and interpreting its significance, wearable-derived heart rate variability can plausibly guide training regimens, offering marginal performance gains.

4.3. Wearable Devices in Sports Cardiology. Wearable technologies for monitoring CVD significantly reduce the costs associated with in-hospital treatments. For continuous and outpatient care, smart wearables enhance diagnostic accuracy, offering athletes with cardiovascular conditions convenient self-care solutions by consistently tracking biomedical variables during daily activities. CVD monitoring methods vary widely, with their effectiveness depending on the specific condition being managed and the monitoring approach used.[126,127] For example, ECG and PPG are typically utilized in fitness bands and smartwatches for ongoing and ambulatory monitoring. ECG, a widely recommended test for monitoring certain heart conditions, records electrical activity from the body's surface. By measuring the electrical potential difference between two points on the body, ECG can detect heart issues such as heart failure and arrhythmias Nevertheless, conventional electrocardiography using electrodes continues to be the best method for assessing heart attack risk. In sport performance, these wearable technologies are instrumental. They allow athletes to monitor their heart health, ensuring safe participation in high-intensity activities. Ongoing surveillance can detect possible problems at an early stage, enabling prompt action and possibly averting severe heart incidents during intense physical activity. Wearables also help tailor training programs by providing real-time data on an athlete's physiological responses, ensuring that training intensity is optimized for both performance and safety. By integrating wearable technology into their routines, athletes can achieve better performance while minimizing the risk of cardiovascular complications.

PPG is an important method for monitoring CVD metrics. This method operates by releasing photons into bodily tissues and examining the light that bounces back. PPG shows improved accuracy when used at the wrist through bands or smartwatches, which athletes with cardiovascular conditions can easily wear during daily activities. However, PPG has limited reliability and robustness during physical exertion or movement. Besides ECG and PPG, other methods like ballistocardiography (BCG) and PCG are also utilized to track vital heartbeat information. BCG measures ballistic forces produced by the heart, generating a graphical representation of the body's repetitive movements caused by blood being ejected into major vessels with each heartbeat.[128,129] BCG is often incorporated into wearables through highly sensitive accelerometers placed on the torso. PCG technology records heart sounds but is highly sensitive to ambient noise, making it less likely to be integrated into current wearable devices.[130] In sports performance enhancement, these technologies offer significant benefits. They allow athletes with cardiovascular conditions to continuously monitor their heart health, ensuring safe participation in intense physical activities. Continuous data collection helps identify potential issues early, enabling prompt intervention and potentially preventing serious cardiac events during exercise. Moreover, these wearables provide valuable insights into an athlete's physiological responses, aiding in optimizing training regimens for both performance improvement and safety. Integrating these wearable technologies into their routines helps athletes enhance their performance while minimizing cardiovascular risks.

The human skin, covering most of the body, offers an ideal platform for noninvasive wearable devices in medical applications. These skin-based devices can monitor both physiological and psychological parameters, particularly beneficial for managing athletes with CVDs. They enable the diagnosis of various conditions by analyzing skin secretions like sweat, providing qualitative and quantitative insights. Epidermal wearables, such as electronic skin (e-skin), directly adhere to the skin like tattoos. E-skin integrates adaptable electronic elements such as conductive substances (for instance, liquid metal alloys, graphene, gold nanorods, or polymers with a rubber base), enabling the gathering of customized medical information.[131,132] Sensors embedded in electronic skin monitor health metrics and send information to smartphones or other connected gadgets instantly.[133] Moreover, e-skin can harness energy from the body's electrophysiological processes, eliminating the need for batteries. Its flexibility and adaptability to body movements make it superior to traditional wearables, ensuring continuous monitoring without discomfort.[134] This innovative technology holds promise in sports cardiology by facilitating the monitoring and diagnosis of arrhythmias, assessing heart function in premature athletes, managing sleep disorders, monitoring brain activity, enhancing personalized care, and athlete performance optimization. It is estimated that over one billion people globally live with hypertension or elevated blood pressure, with a majority in developing nations lacking adequate healthcare infrastructure. Regular blood pressure monitoring is crucial for athletes with cardiovascular diseases, as hypertension often presents without symptoms. The lack of monitoring contributes significantly to premature deaths worldwide. Precise blood pressure monitoring necessitates skilled healthcare workers, emphasizing the importance of e-skin in supporting the WHO's objective to lower hypertension rates by 25% by the year 2025.[135] As healthcare technology evolves to be more compact and intelligent, wearable devices like e-skin aim to integrate seamlessly into athletes' daily routines, minimizing

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disruptions to their daily lives. Currently, e-skin is being enhanced through ongoing research and development. Trends suggest it could become more dependable, precise, and less intrusive compared to conventional techniques. This progress is likely to increase confidence among athletes with cardiovascular conditions, encouraging them to use e-skin for health self-management. In addition, e-skin's advancements can significantly impact monitoring and improving athletic performance by providing accurate and noninvasive health data.

5. APPLICATION OF AI-ASSISTED WEARABLE DEVICES IN SPORTS CARDIOLOGY

As the popularity and sophistication of wearables continue to grow, they are beginning to reshape healthcare, driven by advances in hardware and software technologies. Moreover, advancing artificial intelligence, essential for improving mobile health wearables, relies on analyzing vast data sets with algorithms that utilize different learning methods to identify patterns, a fundamental aspect of diagnostics. By incorporating AI methods and neural networks into wearable devices through signal processing and deep learning, researchers can tackle modern tech issues, enhancing the dependability of mobile monitoring systems and the accuracy of ECG and PPG readings.[136] Numerous major reports have highlighted cardiovascular conditions that have either harmed athletes or stopped them from engaging in sports. Consequently, engineers have designed numerous wearable gadgets to consistently track heart rate and blood pressure, intending to identify critical irregularities that could signal serious heart conditions like arrhythmias.[137−139] Research has demonstrated that artificial intelligence can predict cardiovascular events and their long-term effects, such as heart failure, thereby enhancing the diagnostic capabilities of wearable devices.[140] In summary, incorporating AI and neural networks boosts the efficiency of wearable gadgets and improves the precision of heart-related biomedical assessments. Consequently, as wearable devices become more reliable and accessible, athlete acceptance also rises. Wearables are evolving into practical solutions for athletes to continuously and dynamically monitor cardiovascular health during everyday training. Currently, numerous machine learning techniques are applied in wearable technology. This segment reviews existing research on integrating wearables with machine learning algorithms to enhance sports cardiology. The review categorizes based on machine learning methods. Table 3 provides a summary of the studies employing wearables and artificial intelligence algorithms.

5.1. Applying Supervised Learning Techniques in Wearable Devices. Learning algorithms are categorized into two main types: supervised and unsupervised. In supervised learning, the desired output for training examples is predetermined, and the model is developed using these examples along with their respective outputs.[141] Generally, supervised learning is employed for tasks like classification, where the goal is to associate an input example with a corresponding label, and for regression, which focuses on establishing a relationship between inputs and continuous outputs.[142] In both cases, the objective is to establish accurate relationships between inputs and outputs, seeking a model that can generate correct output data effectively. Nonetheless, the model's performance will be greatly diminished if the training data are flawed or have erroneous labels. Popular supervised learning techniques encompass random forest, Naïve Bayes, artificial neural networks, and support vector machines.[143−145]

Table 3. Overview of Advancements in Wearable Devices and Artificial Intelligence Technologies

Artificial intelligence algorithms	Application	Category of learning techniques	ref.
Random Forest	Detection of physical Fatigue	Supervised learning	176
Long Short-Term Memory	Recognition of human activities	Supervised learning	177
Statistical analysis	Recognition of human activities	Supervised learning	178
Artificial Neural Network	Heartbeat classification	Supervised learning	179
Support Vector Machine	Recognition of stress in construction workers	Supervised learning	180
Convolutional neural networks	Recognition of human activities	Semisupervised learning	181
Random Forest	Recognition of human activities	Semisupervised learning	182
Support Vector Machine	Recognition of human activities	Semisupervised learning	183
Long Short-Term Memory	Prediction of cardiovascular risk	Semisupervised learning	184
Support Vector Machine and Simple 1-NN classifier	Wearable video used for location identification	Semisupervised learning	185
K-means	Detection of poor posture	Unsupervised	186
Expectation Maximization algorithm	Recognition of human activities	Unsupervised	187
K-Means	Recognition of human activities	Unsupervised	188
Spectral clustering, hierarchical clustering	Recognition of human activities	Unsupervised	189
K-Means	Recognition of human activities	Unsupervised	190

Supervised learning techniques are extensively utilized in machine learning for the development of automated systems, especially in enhancing cardiovascular health monitoring for athletes. Saadatnejad et al. introduced a cutting-edge ECG classification algorithm tailored for wearable devices, designed for the continuous surveillance of cardiac health.[146] This method, beneficial due to its low energy usage, utilized several LSTM recurrent neural networks in conjunction with wavelet transform, achieving excellent ECG classification results. In a similar vein, different research introduced a novel ECG classification method tailored for energy-efficient wearable gadgets, utilizing spiking neural networks.[147] This method employed spike-timing-dependent plasticity and reward modulation, adjusting model weights based on spike signal timings. The results indicated its efficacy for real-time operation and highlighted its lower energy consumption compared to other devices, making it ideal for athletes requiring uninterrupted monitoring with minimal recharging intervals. Acharya and Basu focused on developing classification models to detect anomalies in patients' breathing sounds.[148] Their work aimed at enabling the automated diagnosis of cardiovascular and pulmonary conditions. They utilized a deep learning model for categorizing respiratory sounds. Furthermore, they implemented a regional log quantization technique to reduce memory usage, making it ideal for wearable devices with limited memory capacity. For athletes, maintaining optimal respiratory health is crucial for

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performance, and these advancements can be particularly beneficial. Incorporating such models into wearables can help in early detection and management of respiratory issues, ensuring athletes maintain peak cardiovascular and pulmonary health. The efficient use of memory in these devices allows for continuous monitoring without the need for frequent recharges, making them practical for active use.

5.2. Applying Unsupervised Learning Techniques in Wearable Devices. In unsupervised learning, the goal is to discern the inherent structure within unlabeled data. Typical activities in this field involve grouping, estimating density, and learning representations. Techniques such as principal component analysis and autoencoders are frequently utilized for these objectives.[149,150] Unsupervised learning is typically used for exploratory analysis and dimensionality reduction, especially in situations where manual data analysis is impractical. These methods provide initial insights into the data set, aiding in hypothesis testing. Dimensionality reduction simplifies data representation by using fewer features, which involves identifying relationships between features to eliminate redundancy.[151,152] This leads to a more efficient data processing approach with reduced computational demands.

Das et al. introduced a self-learning method to estimate heart rate from ECG data collected by wearable devices.[153] The spatial and temporal characteristics of ECG signals were transformed into spike sequences, which subsequently activated recurrently connected spiking neurons in a liquid-state machine computational framework. A self-regulated analysis, employing fuzzy c-means clustering of neural spike data, was enhanced using particle swarm optimization techniques. This method, which can be effortlessly applied to spiking-based systems, achieved impressive accuracy and remarkably low energy consumption, thus prolonging the battery life of wearable gadgets. This is particularly advantageous for continuous monitoring of athletes, ensuring longer periods of data collection without frequent recharges. Besides, Krause et al. proposed another unsupervised learning algorithm.[154] They developed and evaluated an online wearable system that could autonomously determine user context and predict context transitions. By utilizing statistical methods and machine learning in their graph algorithms, the system successfully represented user context solely with data from a device that has physiological sensors. This capability can enhance the monitoring of athletes' cardiovascular health by providing real-time context-aware insights without external supervision. In addition, an innovative unsupervised deep learning approach was introduced to enhance data preprocessing for wearable sensors.[155] This method required only 11.25 ns for computation, significantly improving recognition performance by optimizing feature selection and extraction. These advancements are particularly relevant for athlete cardiovascular health monitoring, as they allow for faster and more efficient processing of sensor data, enabling real-time insights and timely detection of potential issues.

5.3. Utilizing Semisupervised Learning Methods in Wearable Technology. When there are few labeled examples but many unlabeled ones, both supervised and unsupervised learning methods are ineffective. In these circumstances, semisupervised learning techniques can be beneficial. With a limited amount of labeled data and a substantial amount of unlabeled data, they can be taught to forecast new instances. Labeled data can assist algorithms in utilizing unlabeled data more effectively, leading to significant enhancements in learning accuracy. Gathering annotated data for learning tasks often necessitates specialists. Tagging the samples can be expensive and sometimes unfeasible because of the vast amount of unlabeled data. In this context, the significance of semisupervised learning is evident.[47]

Wearable devices can amass vast amounts of data, but labeling this data is often costly and time-intensive. Thus, it is beneficial to develop methods that maximize the use of unlabeled data while minimizing labeling expenses. Semi-supervised techniques offer a promising solution by effectively combining a small set of labeled data with a large volume of unlabeled data. Ballinger et al. utilized commercially available wearable heart rate monitors to collect information from numerous international users through a smartphone application.[156] They aimed to diagnose different health issues, including elevated cholesterol levels, by employing a multitask LSTM model. They presented two semisupervised techniques that outperformed manually crafted biomarkers from clinical research. Initially, an LSTM was pretrained as a sequence autoencoder, and the resulting parameters were then used to kickstart a supervised training phase with a small amount of labeled data. The alternative approach employed a generated data set for initial training. These advancements are particularly relevant to monitoring cardiovascular health in athletes, as they allow for the efficient use of wearable data to detect potential health issues with minimal manual labeling effort.

Yang et al. described an innovative method to autonomously detect near-miss falls by analyzing a worker's movement data, collected through wearable inertial measurement units (WIMUs).[157] A support vector machine (SVM) algorithm, utilizing semisupervised learning, was used to detect near-miss falls. Two experiments were conducted to gather data on near-miss falls, which were then used to test this method. This method utilizing WIMU technology can identify near-miss falls among ironworkers without disrupting their activities, helping to prevent fall-related incidents. This technology has potential applications in sports cardiology by enhancing athlete safety through continuous monitoring and early detection of fall-related events, which can be crucial for preventing injuries.

Stikic et al. developed an innovative method for recognizing activities by employing a semisupervised learning process.[158] This method employed a combination of minor labeled data sets and extensive unlabeled data sets, disseminating information via a graph that encompassed both data types. They proposed two different methods to combine multiple graphs based on feature similarity. Their study assessed the label propagation quality and the performance of classifiers. This method can be applied to sports cardiology by improving the accuracy of activity recognition in athletes, aiding in the continuous monitoring of cardiovascular health, and the early identification of potential heart-related issues.

To minimize supervision levels, semisupervised learning was applied to improve the recognition of human activities from limited labeled data.[159] This approach allows reducing the effort of supervision to a minimum, while still preserving competitive recognition performance. To develop activity models from a small amount of labeled data, two semi-supervised techniques, self-training and cotraining, were utilized. The study demonstrated that cotraining outperformed self-training by utilizing additional sensor modality information during training. In certain instances, cotraining outperformed fully supervised methods in terms of recognition accuracy. Their proposed method used a pool-based setting, where a

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large amount of unlabeled data was available alongside a small set of labeled data. An expert subsequently labeled the most informative samples chosen by the algorithm. LabelForest offers an alternative method for recognizing human activities.[160] Information gathered from wearable devices frequently includes considerable noise and ambiguity. LabelForest, an adaptable semisupervised learning framework, boosts machine learning algorithm effectiveness by increasing the size of the training data set. It chooses a portion of untagged data for annotation by comparing it to already labeled examples. LabelForest includes two techniques: a spanning forest algorithm for selecting and labeling samples, and a silhouette-based filtering method to add samples with more reliable clustering assignments to the training set. These methods can be highly beneficial for monitoring athletes' cardiovascular health, as accurate activity recognition helps in tracking and managing their physical condition and detecting potential heart-related issues early.

Wiechert et al. utilized a wearable headband called Muse to collect EEG brain signals from participants engaged in various activities, such as reading or listening to music.[161] The goal was to identify both the participants and their activities based on the recorded EEG signals. For this purpose, multiobjective clustering was accomplished using K-medoid clustering in conjunction with an evolutionary algorithm. The genetic algorithm was utilized to determine the optimal K medoids. Wiechert et al. reported that their method outperformed K-means. This approach can be adapted to monitor athletes' brain activity, potentially linking cognitive states with cardiovascular health, thus offering valuable insights for optimizing performance and early detection of stress or fatigue-related cardiovascular issues.

5.4. Applying Reinforcement Learning Techniques in Wearable Devices. Reinforcement learning involves mapping situations to appropriate actions to maximize a numerical reward signal.[162,163] In contrast to supervised learning, reinforcement learning does not provide the learner with the correct action but requires trying various actions in different states to determine the best actions that yield the highest reward. Effective action selection is crucial for maximizing long-term utility, as focusing solely on immediate rewards can result in suboptimal long-term performance. Reinforcement learning challenges can be represented as Markov decision processes (MDPs).

Wearable technologies have incorporated reinforcement learning in various applications, significantly impacting athlete cardiovascular health. For example, ADAS-RL, a modified Q-learning algorithm, continuously adapts Lane Departure Warning System (LDW) interventions by integrating driver behaviors and reactions.[164] This technique modifies alert intervals according to driving habits, assisting motorists in keeping a safe gap of about 1.75 m from lane boundaries. Such adaptive systems could be beneficial in monitoring and responding to athletes' cardiovascular signals during training or competition. FaiR-IoT, an alternative framework based on reinforcement learning, employs Q-learning to ensure adaptive and fairness-conscious human-in-the-loop IoT applications.[165] Assessments covered an intelligent home IoT app and a vehicle driver support system. In a smart home setting, thermostats were regulated automatically by tracking fluctuations in human body temperature over time, a method that could be adapted to monitor athletes' heart rates and maintain ideal training environments. The assistance system for drivers dynamically modified collision alert thresholds by considering individual factors such as reaction time and focus, showcasing the possibility of adapting similar systems for real-time monitoring of athletes' physical conditions. These advancements in wearable technology, particularly with reinforcement learning integration, are crucial for enhancing cardiovascular health monitoring in athletes. By ensuring timely and adaptive responses to their physiological states, these technologies can improve athletes' overall health and performance.

6. CHALLENGES OF AI-ASSISTED WEARABLE DEVICES IN SPORTS CARDIOLOGY

Although AI shows significant promise, challenges persist in fully integrating AI and wearable technologies into clinical practice. A key issue is addressing the various ethical and legal challenges involved.[166,167] Ethically, concerns such as data privacy, algorithmic biases, fairness, transparency, safety, and informed consent must be thoroughly considered. Access to advanced technology, which is not widely available, must also be taken into account. Legally, issues like intellectual property rights, cybersecurity, privacy, data protection, liability, and safety remain highly relevant. Recognizing potential flaws in the design and implementation of AI-driven wearable devices is crucial, especially when monitoring athletes' cardiovascular health. Furthermore, AI models in sports cardiology may be vulnerable to algorithmic biases, which could result in discrepancies in performance predictions across different demographic groups. These biases often arise from imbalanced training data sets and variations in physiological responses among athletes of varying ages, ethnicities, and genders. It is essential to recognize that AI-driven wearables could reinforce existing patterns of discrimination, inequality, and marginalization. The biases inherent in the data used to train algorithms can distort outcomes and perpetuate researchers' assumptions and prejudices.[168,169] Additionally, the implementation of AI-powered wearable solutions in sports cardiology faces regulatory challenges, as current medical device approvals often require extensive validation and clinical trials. While wearables have demonstrated promise in real-time cardiovascular monitoring, the long-term benefits of their use in preventing major cardiac events remain insufficiently supported by large-scale clinical evidence. Further research is needed to establish standardized guidelines for incorporating AI-driven wearable insights into medical decision-making, ensuring their safe and effective use in both competitive and recreational athletes.

As artificial intelligence advances, it becomes increasingly incomprehensible to humans, even to those who designed the algorithms. This opacity poses significant risks in safety-critical fields such as medicine, where incorrect decision-making can endanger lives. The development of explainable artificial intelligence (XAI) aims to address this by making artificial intelligence algorithms more interpretable. XAI allows humans to understand artificial intelligence operations, trust outcomes, identify biases, and evaluate accuracy and transparency.[170] Ensuring that artificial intelligence systems are explainable helps meet regulatory requirements, adhere to best practices, and facilitate deployment in high-risk areas like healthcare.[171,172] The increasing use of intelligent medical gadgets and AI-powered health apps has raised worries about medicine becoming less personal. These intelligent applications are taking over certain roles traditionally performed by physicians. However, the trust issue arises when decision-makers do not

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fully comprehend the artificial intelligence systems they depend on. In cases where there are disagreements in management strategies, doctors should maintain the final say in AI-assisted medical choices.[173] This principle also applies to sports cardiology, where evaluating athletes' cardiovascular health is crucial. Maintaining a balance between human judgment and artificial intelligence integration is vital for fostering a healthy physician-athlete relationship. Artificial intelligence-driven wearable technologies can be beneficial for reducing administrative workloads and enhancing patient care.

7. CONCLUSION

Athletes constantly seek new methods to enhance performance and minimize injuries. The growing capability to gather physiological data aids this goal by enabling personalized training plans and emphasizing the significance of recovery. For both sports cardiologists and athletes, deciphering and utilizing this vast amount of data to distinguish valuable information from irrelevant noise is crucial. With technological progress and more lenient exercise recommendations for athletes with heart conditions, wearables might become crucial devices. These gadgets can oversee the safety of workouts for athletes with heart issues, identify, and even foresee emerging cardiovascular conditions. Although no standardized guidelines currently exist for integrating wearable data into sports cardiology, we foresee three primary applications (Figure 8):

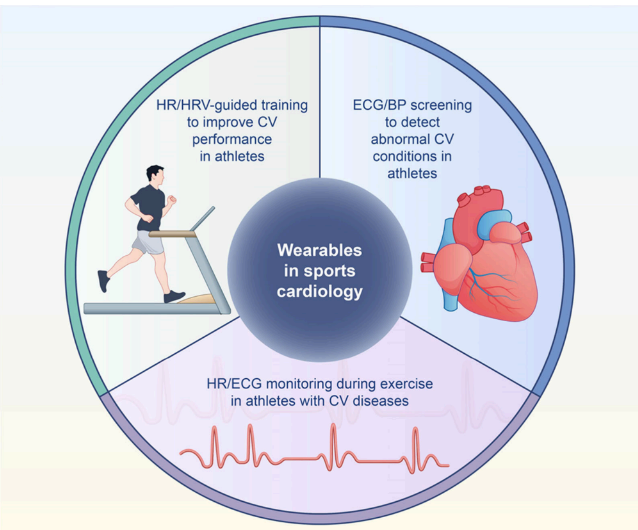

Figure 8. Clinical applications of wearable devices in sports cardiology practice. Abbreviation: HR, Heart rate; AHR, Average heart rate; CV, cardiovascular; ECG, EMG; BP, Blood pressure.

(1) directing exercise regimens for athletes with established cardiovascular conditions, (2) enhancing cardiovascular performance, and (3) screening for cardiovascular disease. This approach will be particularly beneficial in managing the cardiovascular health of athletes, ensuring both safety and optimal performance.

Combining AI with wearable devices has revolutionized sports by delivering instant data during practice sessions and events. These sensors deliver objective physiological information, which previously required costly, specialized equipment. This information is essential for creating specialized training plans, improving competition strategies, and predicting as well as preventing injuries in competitive athletes. The advent of wearable tech has ushered in a new age of data-centric sports coaching, providing trainers and athletes with immediate access to crucial physiological data. Through the use of wearable tech, trainers can collect and interpret extensive data, allowing them to refine training programs and make well-informed choices to enhance performance and reduce the likelihood of injuries. AI-driven coaching platforms could transform how athletes receive guidance and feedback. They examine large amounts of data from wearable devices, offering immediate, data-based insights into an athlete's performance. AI identifies trends, patterns, and irregularities in data, providing tailored suggestions for enhancement. Trainers are responsible for the physical, mental, and technical growth of athletes, in addition to overseeing their performance and well-being. Wearable devices currently provide significant ease in collecting real-time physiological data during workouts or events, allowing for the assessment of internal load metrics that once needed costly tools. The surge in accessible data greatly improves the creation of specialized training regimens, strategic competition planning, and the forecasting and prevention of injuries for athletes. Within sports cardiology and performance, utilizing AI and wearable devices enables accurate tracking and modification of heart and physical metrics, ensuring athletes with cardiac issues can safely reach their potential. Moreover, the development of remote coaching platforms could transcend spatial and temporal limitations in the future.

Despite the increasing reliability of wearables in monitoring heart rate during exercise, traditional clinical methods such as ECGs remain the gold standard for precision and accuracy. Wearable devices may exhibit slight discrepancies in heart rate monitoring due to issues such as sensor placement, motion artifacts, or individual variability in physiology. However, wearables show considerable promise in contexts where continuous, real-time data collection is crucial, such as for endurance athletes or those in remote locations where access to clinical facilities is limited. In high-intensity sports, such as running or cycling, wearables can offer valuable insights into heart rate dynamics during prolonged exertion, while traditional methods may be impractical or intrusive for such activities. Therefore, wearables can be particularly advantageous for long-term monitoring or for athletes with chronic conditions who require ongoing assessment.

Even with progress in AI and wearable tech, the crucial function of human coaches in the athlete-coach relationship remains indispensable. This connection goes further than data analysis, encompassing guidance, encouragement, and emotional backing. The combination of human coaching and artificial intelligence-driven systems can potentially elevate athlete development and performance to new heights. A new study underscores the vital significance of coaches' physical, technical, tactical, and strategic abilities, as well as their capacity for self-reflection, responsiveness to feedback, and display of emotional resilience and neuropsychological insight.[174,175] Sportspeople rely on their trainers for mental encouragement and spoken guidance throughout practice sessions and events. Effective communication and verbal feedback from coaches significantly enhance both athletic performance and social-emotional learning. Wearable sensors are vital in sports cardiology and performance, especially for athletes with heart issues, as they help track cardiovascular health and physical parameters. These devices provide real-time data that can inform training adjustments and ensure safe performance thresholds. However, it is important to recognize

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that while wearable sensors can serve as valuable assistant coaches by providing objective data and insights, they cannot replace the holistic support human coaches offer. This synergy between technology and human expertise maximizes performance potential and ensures the well-being of athletes.

To sum up, incorporating AI and wearable devices into sports cardiology presents many opportunities to improve the assessment and management of athletes' heart health. AI technologies, such as machine learning, present opportunities for better risk stratification, diagnosis, treatment planning, and monitoring in this specialized field. AI can greatly benefit sports cardiology by utilizing cutting-edge imaging methods, genetic analysis, and state-of-the-art wearable technology. Nonetheless, it is essential to tackle moral and legal concerns, guaranteeing openness, equity, and confidentiality in the deployment of AI-powered wearable devices. Integrating doctors' knowledge with AI-powered wearable devices will enhance patient treatment, yield better results, and provide greater insights into athletes' intricate heart health. With the ongoing advancements in AI and wearable tech, essential elements like research, cooperation, and regulatory guidelines will be crucial for fully harnessing the transformative power of these innovations in sports cardiology.

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