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Advanced Wearable Biosensors for Real-Time Health Monitoring: From Functional Materials to Intelligent Clinical Applications

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Abstract
Wearable biosensors (WBSs) are transforming health monitoring by enabling continuous, non-invasive assessment of physiological and biochemical parameters outside conventional clinical settings. This chapter presents the fundamental principles of wearable biosensing and examines recent advances in biorecognition strategies, sensing architectures, and functional materials that support reliable real-time monitoring. Attention is given to hydrogels, nanomaterials, and conductive polymers because of their roles in flexibility, biocompatibility, sensitivity, and signal transduction. The chapter discusses the detection of clinically relevant biomarkers and physiological signals, while highlighting key challenges associated with signal fidelity, including environmental interference, sensor drift, biofouling, and motion-induced artifacts. Approaches for improving signal quality through optimized materials, device design, signal-processing strategies, and data interpretation are also considered. Furthermore, the integration of artificial intelligence (AI) and the Internet of Things (IoT) is explored as an important pathway toward intelligent, connected, and personalized health monitoring. The chapter concludes by addressing major challenges involved in translating wearable biosensor technologies from laboratory prototypes to clinically meaningful applications, including analytical reliability, scalability, interoperability, data security, and clinical validation. Collectively, these advances position WBSs as promising tools for personalized and remote healthcare, with potential to complement conventional diagnostic approaches and support earlier, data-driven health interventions and longitudinal monitoring across diverse patient populations and real-world conditions.

Keywords: Wearable Biosensors; Real-Time Health Monitoring; Functional Biomaterials; Biomarker Detection; Signal Processing; Artificial Intelligence; Personalized Healthcare

Introduction
With the fast-paced lifestyle that everyone lives in the modern world, especially the working class, people tend to forget about maintaining their health and fitness. Traditional healthcare involves several clinic visits for diagnosis, testing, and treatment, which is time consuming and means that people only get medical help when they are sick. Therefore, there is a growing need for wearable devices that will be able to continuously monitor health in real-time and give users and healthcare

professionals real-time health insights (Xu et al., 2014). WBSs are progressively used in monitoring healthcare by detecting diseases early, health conditions, supporting medical diagnosis, and assessing health of a person by analyzing body fluids because they can constantly measure important biomarkers (Sharma et al., 2021). They have captivated great attention by providing continuous, real time, and noninvasive monitoring (Kim et al., 2019). These sensors can measure physical parameters such as heart rate, body temperature, blood pressure, and ECG, as well as chemical marker like glucose, lactate, cortisol, sodium, and potassium from body fluids such as sweat, saliva, tears, blood, and interstitial fluid (Xian, 2023).

Compared with traditional healthcare methods, which are often costly and give only periodic assessments of health, these sensors provide low-cost, non-invasive solutions for continuous monitoring of health. They allow real-time collection of data, remote patient care, and timely medical intervention, making health care more accessible and efficient (Shajari et al., 2023). Developments in sensor technology have made them more accurate, relaxing, and trustworthy for individualized healthcare. Many wearable biosensors use wireless communication and IoT technology to transmit health data to smartphones or computers for analysis, and Artificial neutral networks (ANN) are frequently used to process this data and give meaningful health perception and personalized feedback (Smith et al., 2023). They play a vital role in managing chronic diseases such as diabetes and cardiovascular diseases by facilitating constant remote monitoring of health and minimizing the demand for repeated hospital visits. When merged with AI and machine learning, they can foresee potential problems of health early, while also assisting individualized and preventive healthcare through continuous monitoring of physical activity, sleep, and overall health. Despite remarkable advancement, these sensors still face challenges that are related to long-lasting stability, data protection, interoperability, regulatory authorization, and clinical verification.

Continued advancement in materials, device design, and digital technology of health is predicted to overwhelm these limitations and support broader clinical adoption (Vo & Trinh, 2024). This chapter gives a comprehensive overview of wearable biosensors for real-time monitoring of health. It starts by explaining the fundamentals of wearable biosensors, including their working principles, types, components, advantages, and limitations. The chapter then discusses advanced materials used in wearable biosensors, factors that affect signal fidelity and performance, and their application in physiological, biochemical, and disease-specific monitoring. Moreover, it explains how AI and smart technologies are used in WBSs. It also describes their use in healthcare, commercialization, and regulatory requirements. Finally, the chapter highlights emerging technologies, future research directions, and the potential of WBSs to advance individualized healthcare.

Fundamentals of Wearable Biosensors

A Biosensor uses biological molecules like enzymes, antibodies, nucleic acids, or cells to recognize a target analyte with a high degree of specificity before converting it into a measurable signal (Weber et al., 2026). There are various types of biosensors that are different in terms of type of reaction and output. The two major types are enzyme-based catalytic biosensors and DNA and antibody-based affinity biosensors. WBSs are small electronic devices that can be worn on or placed in the body that detect and can be designed as smart tattoos, gloves, clothing or implantable devices that detect biochemical markers in body fluids such as sweat, saliva, tears, and interstitial fluid and transmit the collected data to portable devices for real-time analysis (Sharma et al., 2021). The following three elements are important components of the WBSs:

- Biorecognition element
- Transducer

- Signal amplifier

The working principle of WBSs consists of four basic steps. First, the biorecognition element recognizes the target analyte through biological molecules like antibodies, enzymes, whole cells, polymers, or aptamers. Second, the interaction of the analyte and the biorecognition element is transformed into a measurable signal (electrical, optical, thermal) by the transducer. Third, the signal amplifier and processing processes and amplify the generated signal, enabling it to be presented and explained accurately for monitoring of health. Finally, the processed data are sent wirelessly to a smartphone or other digital device for real-time surveillance and analysis (Pillai et al., 2021). WBSs can be classified using different approaches. These classifications are based on their design, the type of biofluid or bio analyte they monitor, and the transduction mechanism used. Based on their design, WBSs include head-mounted biosensors, body-worn biosensors, wristband biosensors, smartwatch-based biosensors, patch-based biosensors, dermal tattoo biosensors, ingestible pills, and electrochemical and physiological biosensor systems for brain activity monitoring (Weber et al., 2026).

Based on the biofluid or bioanalyte analysis, WBSs are categorized as tear-, saliva-, sweat-, and interstitial fluid-based biosensors. They can be classified according to their invasiveness as subcutaneous and implantable biosensors, which constantly monitor physiological biomarkers for assessment of health (Pillai et al., 2021). Based on the transduction mechanism, WBSs are further classified into electrochemical, optical, and piezoelectric depending on how biological recognition event is converted into measurable signal (Heikenfeld et al., 2018). WBSs give quick and continuous monitoring of health anytime and anywhere, which helps doctors in the diagnosis of disease, its treatment, and improve care of patient (Arakawa et al., 2022). They support people, especially those with chronic diseases, to track their health, minimize visits to the hospitals and costs of treatment, and seek medical care when required. They can monitor vital signs, e.g., activity of heart, temperature of body, levels of oxygen in blood, supporting better management of health and fitness (Smith et al., 2023).

Advanced Materials for Wearable Biosensors

The efficiency of the WBSs highly depends on the materials from which WBSs are made (Yang et al., 2017). Materials are classified into polymers, nanomaterials, intelligent textiles, conductive inks, and hydrogels. Each material has unique characteristics that enhance precision of sensors, sensitivity, mechanical durability, and biocompatibility. Therefore, choosing the right material is vital to creating WBSs that provide accurate, continuous real-time monitoring of health. The main materials and their key features are illustrated in Table 1 (Vo & Trinh, 2024). WBSs are designed in such a way that they should be thin, flexible, stretchable, and lightweight so that they can easily fit the natural movement of the body without causing distress. Advancements in miniaturization have made these sensors smaller while preserving their performance, making them easier to wear and allowing multiple sensors to be integrated into a single device (Rodrigues et al., 2020; Tricoli et al., 2017).

Table 1: *Comparison of Advanced Materials Used in Wearable Biosensors (Vo & Trinh, 2024; Vo et al., 2024)*

Materials	**Examples**	**Advantages**	**Limitations**
Flexible Polymers	PDMS, PI, PET, Ecoflex	Flexible, lightweight, biocompatible, facile	Poor electrical conductivity, mechanical degradation.

		processing, skin conformity.	
Hydrogels	PVA, Alginate, PEG	High water content, tissue-like structure, biocompatible.	Water loss, poor stability over time.
Smart Textiles	Conductive fabrics	Comfortable, breathable, washable.	Unstable signal after washing.
Conductive Polymers	PEDOT: PSS, PANI, PPy	Electrical conductivity, flexibility, inexpensive.	Instability, delamination.
Graphene	Graphene oxide (GO), rGO	Large surface area, conductivity, flexibility.	Agglomeration, poor dispersion in water.
Carbon Nanotubes	SWCNTs, MWCNTs	Large surface area, conductivity, sensitivity.	Difficulty in functionalization, agglomeration.
Metal Nanoparticles	AuNPs, AgNPs, PtNPs	Signal amplification, catalysis.	Instability in electric current.
Metallic Nanowires	Silver, Gold	High electrical conductivity, fast signal response.	Oxidation, decreased electrostatic potential.
MXenes	$Ti_3C_2T_x$	Hydration capacity, high electrical conductivity.	Oxidation during storage.
Mesoporous Silica	SBA-15, MCM-41	Large pore volume, adjustable pore size.	Poor colloidal stability.
Indium Tin Oxide	ITO films	Transparent, conductive	Slow electron transfer, brittle

Note: PDMS = Polydimethylsiloxane, PI = Polyimide, PET = Polyethylene terephthalate, PVA = Polyvinyl alcohol, PEG = Polyethylene glycol, PEDOT:PSS = Poly(3,4-ethylenedioxythiophene):poly(styrene sulfonate), PANI = Polyaniline, PPy = Polypyrrole, rGO = Reduced graphene oxide, SWCNTs = Single-walled carbon nanotubes, MWCNTs = Multi-walled carbon nanotubes, AuNPs = Gold nanoparticles, AgNPs = Silver nanoparticles, **SBA-15 = Santa Barbara Amorphous-15, MCM-41 = Mobil Composition of Matter No. 41,** PtNPs = Platinum nanoparticles, ITO = Indium tin oxide, $Ti_3C_2T_x$ = Titanium carbide MXene

Multi-Modal Physiological and Biochemical Monitoring

Physiological Signals

The physiological signal monitoring technology makes use of continuous monitoring of both electrical and optical signals produced by the human body for physiological functioning analysis. Examples of physiological signals include electrocardiogram (ECG), electromyogram (EMG), electroencephalogram (EEG), and photoplethysmogram (PPG). These signals represent physiological activities such as cardiac function, muscle activities, brain function, and blood flow, respectively. In the past, measurements of these signals were conducted using equipment from hospitals that were connected to individuals through wires. With recent developments in biosensors, such physiological signals can now be measured continuously through portable and wireless devices (Kim et al., 2024).

Electrocardiogram (ECG) is a diagnostic procedure that measures the electrical activity of the heart. It is very common to recognize heart diseases such as arrhythmia. The ECG wave consists of three vital components: the P wave, QRS, and T wave (Boineau et al., 1978; Clifford & Azuaje, 2006; Pal & Mitra, 2010). ECG WBSs allow continuous monitoring of the heart to provide an ongoing analysis of cardiac performance (Kim et al., 2024).

Electromyogram (EMG) is an analysis technique that is used to measure the electrical signal produced by muscles during contraction. It is commonly used in research and diagnostics of muscles work and activity of the neuromuscular system. EMG is a method that is used in rehabilitation medicine, exercise physiology, prosthesis control, and diagnosing neuromuscular diseases (Turker, 2013). EMG WBSs uses flexible electrodes for monitoring of muscle activity during daily activities (Daube & Rubin, 2009).

Electroencephalogram (EEG) is a painless technique of measuring the electrical activity of the brain. It is used for the study of brain function, the process of cognition and diagnosis of neurological disorders like epilepsy and sleep disorders (Kumar & Bhuvaneswari, 2012). Recently, there was a development of a recording system in EEG WBSs to improve comfort and allow monitoring of brain activity in real-life situations (Kim et al., 2024).

Photoplethysmogram (PPG) is an optical technique that recognizes the variations in the volume of blood through light-emitting diodes and photodiodes. It is a widely applied technique for monitoring heart rate, blood oxygen level, and blood circulation (Ryals et al., 2023). Due to low-cost, simplicity, PPG WBSs has emerged as one of the popular sensing methods (Kim et al., 2024).

Respiratory Rate refers to breathing frequency per minute, and it is one of the important signs that give an assessment of functioning of the respiratory system. Normal respiratory rate in healthy adults is between 12 and 20 breaths per minute. An abnormality in respiratory rate may indicate a respiratory or cardiovascular condition and be considered a warning of worsening of the clinical state (Hussain et al., 2023). Monitoring of the respiratory rate is important in the diagnostics and treatment of various diseases like asthma, chronic obstructive pulmonary disease (COPD), sleep apnea, and COVID-19 (Ebell, 2007; Miller et al., 2020). Real-time monitoring of breathing through wearable respiratory biosensors is helpful for diagnosing diseases, remote monitoring of patients, and providing medical assistance. Such biosensors are also helpful in monitoring by analyzing the respiration patterns (Hussain et al., 2023).

Body Temperature is a vital physiological factor that shows how well your body regulates its thermal balance and your general state of health. The constant tracking of body temperature helps prevent heat-related illness (HRI) from occurring and allows detecting the beginning of any HRI at an early stage (Dolson et al., 2022). An ideal core body temperature (CBT) for a relaxed state is around 37°C. On the other hand, an increase in temperature to 38.5°C due to exercising can be described as a normal physiological process (Périard et al., 2021; Walker et al., 1976). But when CBT crosses forty°C or more, there is a chance of developing serious HRI, particularly heat stroke, which requires quick medical treatment. With the help of wearable body temperature biosensors, it can track CBT constantly, which allows detecting any abnormalities in temperature levels during physical activities. As compared to traditional temperature measurement methods, WBSs allow for monitoring temperature continuously without any risks to your health and are easy for use by athletes, military service members, workers, and any people who are at risk of developing HRI (Dolson et al., 2022).

Biochemical Signal

Biochemical signal monitoring consists of constant monitoring of biomarkers in biological fluids to determine physiology and metabolism in an individual’s body. Biochemical biomarkers differ from physiological signals because they offer direct insights into the metabolic activities, development of diseases, hydration, and stress of the body. The recent innovations in WBSs have helped in monitoring the biomarkers in biofluids that are easy to obtain. These biofluids include sweat, saliva, tears, and interstitial fluid (ISF), which consists of different biomarkers such as glucose, lactate, cortisol, electrolytes, proteins, hormones, and metabolites for continuous monitoring of one’s health without the use of blood (Heikenfeld et al., 2019; Kim et al., 2019).

Biochemical Biomarkers

Glucose is one of the crucial biochemical markers that are being monitored using WBSs, as it holds significant importance in terms of metabolism and management of diabetes. Continuous Glucose Monitoring (CGM) offers real-time information about glucose levels, which helps both patients and healthcare providers in managing diabetes better than the usual prick-and-test method of blood glucose level measurement. Glucose biosensors worn on the body are capable of constantly monitoring the glucose levels in biological fluids, including interstitial fluid, sweat, saliva, tears, and urine. Thus, making bloodless sampling possible (Johnston et al., 2021).

Lactate is one of the significant biochemical markers which are related to the energy metabolism of cells. Elevated levels of lactate could be due to hypoxia, metabolic problems, or strenuous physical exercise (Ding et al., 2025). Hence, continuous monitoring of lactate is of great significance for use in sports medicine, physiology of exercise, treatment of trauma cases, and disease management. Wearable lactate biosensors used for monitoring lactate do so in sweat without causing any invasiveness. The latest development in lactate monitoring involves the integration of electrochemical sensors with microfluidic systems and wireless electronic devices for mobile applications (Xuan et al., 2023).

Cortisol is a steroid hormone produced by the body in reaction to both physical and psychological stressors. Though normal amounts of cortisol are vital in maintaining homeostasis, an increase in the production of this hormone is linked to diseases such as stress, anxiety, and depression. Thus, cortisol is known to be an essential biomarker for stress monitoring purposes. Free cortisol may be measured in various biological fluids like sweat, saliva, urine, tears, and Interstitial fluid (ISF) and is hence ideal for use in non-invasive biosensors for wearable devices. New developments in wearable electrochemical biosensors have made it possible to continuously measure cortisol through flexible sensing technology and wireless data transfer (Ok et al., 2024; Samson & Koh, 2020; Sekar et al., 2020).

Electrolytes are essential minerals that serve a critical function in regulating water balance, neural transmission, muscle contraction, and organ functions. Imbalances in electrolytes can lead to various disorders including hypertension, heart failure, and renal diseases. Sweat has several electrolytes which can be analyzed without invasive techniques. Therefore, it is a promising biofluid for the development of WBSs. WBSs for electrolyte measurements allow for continuous and simultaneous detection of different electrolytes within the sweat. Recent developments in flexible and cost-effective wearables have increased the use of electrolyte monitoring in healthcare (Kim et al., 2021).

Biological Fluids Used for Wearable Biochemical Sensing

Saliva is an easily obtainable bodily fluid that consists of numerous biomarkers including proteins, hormones, drug metabolites, glucose, electrolytes, and pH-related substances. Since many salivary biomarkers are interchanged with the bloodstream, the use of saliva can substitute blood for disease diagnostics and health monitoring in a non-invasive way. Wearable saliva biosensors can trace multiple biomarkers and have been proposed to be used in disease diagnostics such as COVID-19.

Sweat is one of the most researched biofluids that can be used for wearable biosensing due to the possibility of non-invasive collection of bodily fluid on a continuous basis. In addition to glucose, lactate, and electrolytes, sweat includes many other biomarkers reflecting the metabolic and physiological state of the body. Real-time tracking of these biomarkers through wearable sweat biosensors has a wide range of applications in sports, hydration assessment, stress monitoring, and disease management.

Tears consist of several kinds of biomolecules such as proteins, electrolytes, glucose, sugars, organic acids, and other components, which show a lot about eye health. Changes in the composition of tears might show that there is a problem either in the eyes or other organs. Biosensors in the form of smart contact lenses are designed for the analysis of tear composition and the diagnostics and treatment of ocular diseases.

Interstitial Fluid (ISF) is a biological fluid situated under the skin and containing different types of biomarkers like blood ones. Due to this similarity, ISF has become popular for continuous monitoring of health. Most WBSs make use of microneedles to get ISF and identify biomarkers such as glucose and β-hydroxybutyrate, which allow monitoring of metabolic diseases such as diabetes (Song et al., 2023).

Signal Fidelity in Wearable Biosensors

Signal Fidelity refers to the ability of WBSs to correctly capture and retain physiological or biochemical signals with minimal distortion or data loss. One of the keys aims of using WBSs is that of securing high signal fidelity, because correct data are important for health monitoring and treatment decisions (Stuart et al., 2022; Suryaprabha et al., 2026). A number of methods can be used to achieve signal fidelity, including signal acquisition, motion artifact reduction, noise reduction, calibration, performance testing, and signal improvement through machine learning are demonstrated in Figure 1.

Signal Acquisition: It is the first step in the process of WBSs technology, whereby biological and biochemical signals are measured and transformed into electrical signals that are ready to be analyzed. WBSs can measure various biological signals, among which include bioelectrical signals, breathing, physical movements, heartbeat, glucose levels, and other biomarkers. There are three crucial components of the data acquisition procedure, namely the sensing probe, signal conditioning, and analog to digital converter (ADC). First, the sensing probe transforms biological signals into analog electrical signals. After that, these signals pass through the signal conditioning process and are turned into digital form by the ADC, and only after that are sent to an external device, like a smartphone or a computer (Liu et al., 2022).

Motion Artifacts Reduction: Motion artifacts represent one of the primary sources of interference in WBSs, which decreases the signal fidelity and impacts the precision of measuring the physiological parameters. Such artifacts are caused by body movements associated with the displacement of the sensor with respect to the skin, changes in the skin-electrode interface, mechanical deformation of the underlying tissues, as well as the displacement of cables and other components of the device, causing an undesired interference which may partially overlap with the target biological signal. The problem of motion artifacts lies in the fact that their frequency range is quite similar to the frequency range of biological signals; therefore, filtering may not be sufficient to remove them completely. As a result, they can negatively affect the precision of real-time monitoring of physiological parameters during physical activity. To reduce the impact of motion artifacts, different techniques such as adaptive filtering, wavelet transformation, empirical mode decomposition (EMD), independent component analysis (ICA), spectrum subtraction, blind source separation (BSS), and multichannel measurement have been applied. More recently, machine learning approaches have been proposed to detect and eliminate artifacts as well (Boyer et al., 2023; Khalili et al., 2024; Seok et al., 2021).

Noise Reduction: Physiological signals captured using WBSs are typically weak and very vulnerable to interference from noise produced by motion, electrode contacts, power line noise, and high-frequency noise in the environment. This makes noise reduction very important as part of signal processing, which aims at ensuring reliable measurements. Noise reduction in WBSs is accomplished through signal conditioning that involves amplification and filtering of signals. Amplifiers amplify weak physiological signals and reduce the effect of common mode noise to improve signal quality. Filters eliminate unwanted noise elements in the signal while keeping the useful physiological signals. Analog and digital filters are used in WBSs, where Butterworth, Chebyshev, and Elliptic filters are usually used depending on the nature of the signal and noise (Liu et al., 2022).

Sensor Calibration: It is a critical process to guarantee the proper functioning of WBSs for obtaining reliable readings. Calibration requires the validation of proper signal measurement and minimization of variations among different WBSs. There are two main categories of calibration, including unit calibration and value calibration. Unit calibration is necessary to verify that different WBSs measure signals properly, while value calibration allows conversion of sensor signals to physiological measurement using certain algorithms. During value calibration, signals are measured for various physical activities carried out by several subjects, and the results are compared with reference measurements to generate predictive models. To enhance the accuracy of WBSs, calibration must involve a diverse sample of subjects and activities of varied intensity levels.

Performance Evaluation: It is done after the calibration process to check if the WBSs provide an accurate measurement of the required physiological parameters. Evaluation is done by comparing the values produced by WBSs to the reference values that are already in existence. The aim of validation is to establish the performance accuracy of the biosensor in performing that for which it is designed. There are different types of validation techniques, such as indirect calorimetry, room calorimetry, doubly labeled water, and direct observation, among others (Bassett et al., 2012).

Machine Learning for Enhancing Signal: Machine learning **(**ML) is an increasingly vital technique in enhancing WBSs by using complicated data from WBSs to transform the collected raw signals to useful health information. ML algorithms can analyze massive biosensor data and recognize patterns, which help enhance the understanding of physiological and biochemical signals obtained from WBSs. ML algorithms perform signal processing operations, including noise reduction, feature extraction, pattern recognition, classification, and prediction of data to ensure more precise monitoring. ML increases the sensitivity, reliability, and performance of WBSs. In addition, ML allows real-time data analysis in IoT-integrated WBSs (Chin et al., 2025).

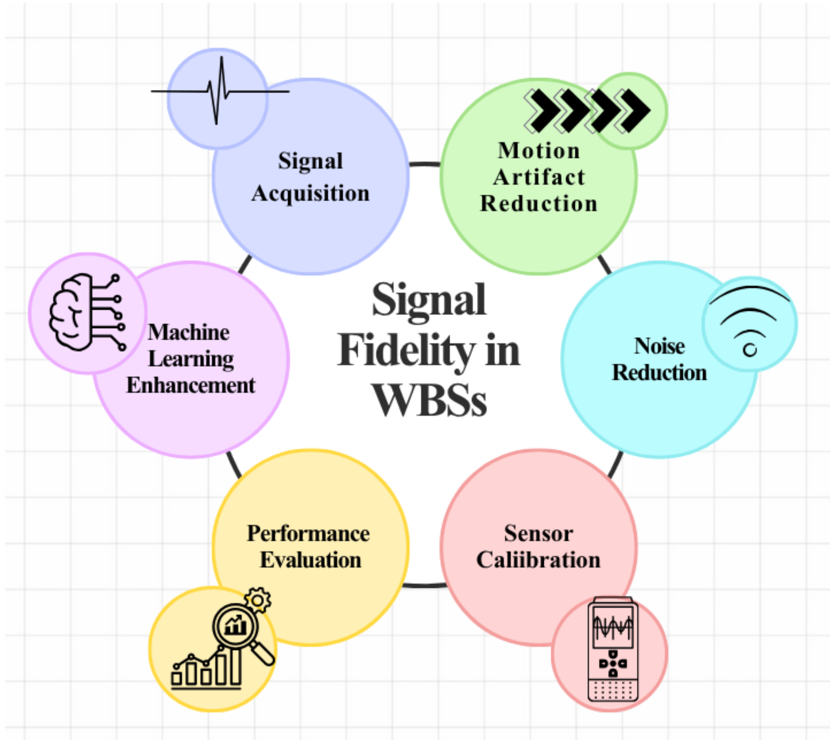

Figure 1: *Conceptual framework of signal fidelity in WBSs*

Device Integration and Wearable Platforms

The following is a wide variety of WBSs that have been designed to serve specific purposes:

- **Patch-type biosensors** are mainly designed as a flexible type of biosensor, such as a soft type, and can be attached to the skin to measure various types of physiological parameters, i.e., heart rate, body temperature, human sweat, etc., in real time (Song et al., 2023).
- **Textile-type biosensors** are integrated into clothing or even fabrics and can be used to monitor various physiological parameters in everyday life (Song et al., 2023).
- **Wearable tattoo biosensors**, also known as electronic tattoos (e-tattoos), are designed and developed as ultra-thin, flexible, and skin-conformal biosensors, which can measure a variety of physiological signals. These biosensors can measure various signals, i.e., body temperature, ECG, EMG, and even components in human sweat, such as metabolites, etc (Gogurla et al., 2021; Kim et al., 2015; Laurila et al., 2022; Mishra et al., 2018).
- **Microneedle biosensors** are designed with microscopic needles, which can penetrate the outer layer of the skin with minimal pain to measure biomarkers or drugs in interstitial fluid (Sun et al., 2023).
- **Contact lens biosensors** measure tear fluid that contains various biomarkers, i.e., glucose, proteins, pH, and nitrite ions, etc., for disease monitoring (Moreddu et al., 2020).
- **Mouthguard biosensors** measure saliva, which contains various biomarkers, including glucose, uric acid, thiocyanate, hydrogen sulphide (H_2S), and N-epsilon- (carboxymethyl) lysine, for health monitoring of oral and/or systemic diseases and/or health conditions (Arakawa et al., 2020; Ciui et al., 2019; Ma et al., 2022; Sangsawang et al., 2021).

The WBSs can provide continuous health monitoring in a non-invasive and real-time manner with the wearer's comfort (Song et al., 2023).

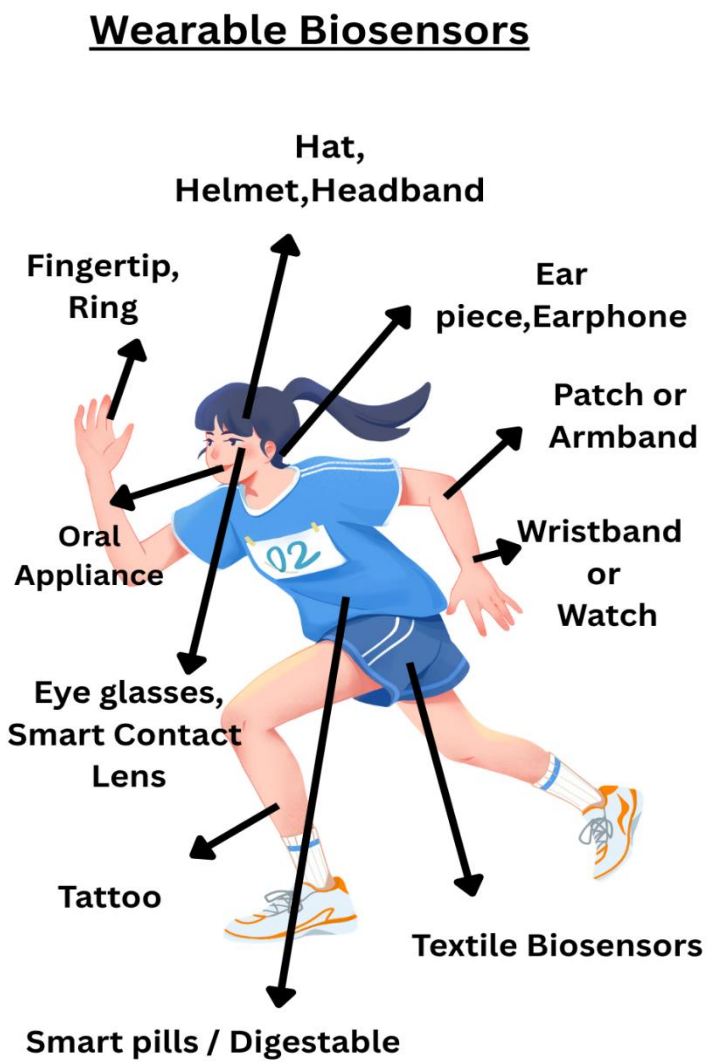

Figure 2: *Examples of WBS platforms including biosensors based on patches, textiles, tattoos, microneedles, contact lenses, and mouth guards*

Artificial Intelligence and Intelligent Wearable Systems

Wearable biosensing systems can be integrated into intelligent devices like smartwatches, fitness bands, and smart clothing for tracking different parameters of health (Polat et al., 2022). Furthermore, WBSs uses wireless communications like Bluetooth and NFC for transferring the data to smartphones or cloud-based server for further processing (Phan et al., 2022). This makes WBS more comfortable for patients and thus makes WBS feasible for regular health monitoring (Vo & Trinh, 2024). In combination with IoT, WBSs provide the opportunity for continuous data communication and remote patient monitoring (Kim et al., 2024). With the use of Artificial Intelligence (AI) and machine learning, there have been significant advancements in WBSs, making them highly precise and personalized (Jin et al., 2020). The major role of AI in WBSs is summarized in Figure 3.

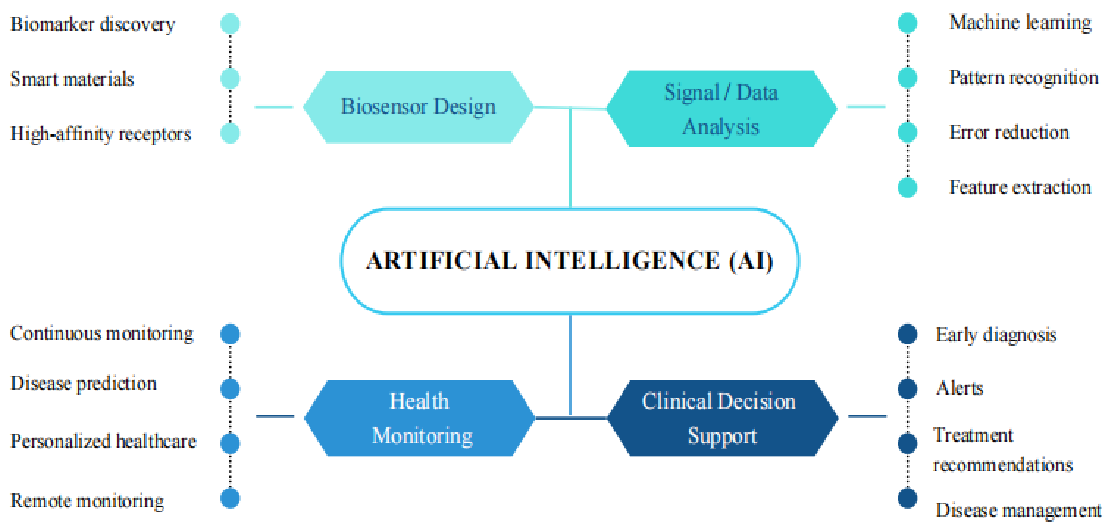

Figure 3: *Role of Artificial Intelligence in wearable biosensors (WBSs)*

The analysis of historical and current physiological data by AI assists in identifying patterns that can cause health problems (Shajari et al., 22023; Zhang et al., 2023). The more data AI receives, the more it learns, and the more accurately it predicts health outcomes (Bustos-Lopez et al., 2022; Nurmi & Lohan, 2021). With the integration of AI, these biosensors can analyze data collected from health-related records and identify patterns that may arise in the future in relation to an individual's health. The intelligence of AI is gained by collecting patients' health data over a period (Vo & Trinh, 2024). Using AI, healthcare practitioners can recognize irregularities such as abnormal heart function and changes in glucose levels, helping patients seek appropriate medical care.

Machine learning enhances the accuracy of biomarker detection in saliva and sweats by reducing errors during the analytical process (Cui et al., 2020; Kadian et al., 2023; Tu et al., 2020; Zhang et al., 2021). Moreover, AI-powered WBSs can identify abnormalities in heart rate or oxygen saturation and immediately notify the individual (Buke et al., 2015; Vaquer et al., 2021). With the use of AI-powered WBSs, individuals can also receive personalized recommendations for maintaining good health based on factors such as exercise and diet (Ji et al., 2021; Singh et al., 2022). These technologies not only provide feedback but also help monitor health status and alert users to potential health problems (Jin et al., 2023; Noorbergen et al., 2019). As AI and machine learning techniques are integrated with optical and electrochemical sensors, significant improvements have been achieved in disease diagnosis (Sankhala et al., 2022; Zhou et al., 2024). In general, the integration of AI, ML, and IoT technologies has made WBSs more advanced in terms of disease prediction, personalized healthcare, and remote patient monitoring.

Clinical Application

- **Early Detection of Diseases:** With the use of WBSs, diseases are early detected by monitoring the specific biomarkers of diseases present in the biofluids (Zhang et al., 2023).
- **Cardiovascular Function:** The monitoring of cardiovascular function through the continuous monitoring of parameters like ECG, heart rate, and blood pressure is done through WBSs. They can detect any abnormalities of the cardiovascular system early enough (Tang et al., 2023).

- **Respiratory Disease Monitoring:** WBSs are used for monitoring respiratory functions like SpO_2 and respiratory rate. This will help the patients to detect respiratory diseases early, including COPD, asthma, and COVID-19 (Aliverti, 2017; Chen et al., 2022).
- **Diabetic Disease:** The continuous glucose monitors (CGMs) can detect the level of blood sugar of the patients, which assists them in better insulin management and proper intake of diet. This helps in avoiding complications from hypoglycemia and hyperglycemia (Vo & Trinh, 2024).
- **Physical Activity and Obesity Management:** WBSs monitor physical activity, energy expenditure, and calorie intake to promote healthy lifestyles. Continuous monitoring helps with weight management, motivates regular exercise, and reduces the risk of obesity-related diseases (Liu et al., 2023; Smith et al., 2023).
- **Medication Adherence and Treatment Compliance:** WBSs help in improving medication adherence through reminders, detection of non-consumption, and monitoring compliance with recommended treatment regimens. This is very helpful to patients suffering from chronic diseases where patients must take medication for long periods of time (Nguyen et al., 2023).
- **Remote Patient Monitoring:** Through WBSs, patients can be remotely monitored on their vital signs and health indicators. This way, healthcare professionals will be able to monitor patients without having to make constant visits to the hospitals. This technology is very useful for the elderly, patients with mobility limitations, and patients having in remote regions (Maganzini et al., 2022).
- **Therapeutic Drug Monitoring:** WBSs help with therapeutic drug monitoring through continuous measurement of levels of drugs such as insulin and warfarin. This allows for adjustment of the dosage in a personalized manner (Liu et al., 2024).
- **Smart Drug Delivery Systems:** WBSs can be used together with smart drug delivery systems to deliver drugs based on measurements of physiological parameters. Closed-loop insulin delivery is one of the examples that have been developed, while others are in the process of development (Zhang et al., 2024).

Clinical Translation

The clinical translation of WBSs refers to the transition of WBSs from laboratory experimentation to clinical practice. Prior to using WBSs clinically, these devices must ensure reproducibility, rapid stabilization, and reliability in clinical situations. WBSs must be able to detect biomarkers within the concentration range of interest and not only in ultra-high concentrations. The stable operation of WBSs must be maintained in a state of dynamic changes in physiological conditions. Clinical translation starts with Institutional Review Board (IRB) approval and the conducting of pilot clinical trials to assess the feasibility and safety of devices in healthcare settings. Further, successful WBSs must go through clinical trials Phase I–III and achieve regulatory approval such as FDA clearance, which usually takes 3-7 years.

Now, WBSs are widely used for continuous health monitoring, but efforts to use them for disease detection and therapy are being conducted. Clinical development over long periods are also based on a stable manufacturing process, repeatable anti-fouling coatings, and effective sensing. WBSs can collect valuable physiological information constantly, generating big data for AI-based clinical decision-making. However, AI should be regarded to eliminate background noise, structure the data, and find clinical patterns, rather than increase the accuracy of sensors. Hence, sensor accuracy and reliability should be optimized when designing WBSs. In the future, the use of the technology in medicine is going to benefit from advancements in multiplex biosensing, anti-fouling materials, better reproducibility, and integration in WBSs. These innovations would allow for the metabolic monitoring of patients, more effective disease management, personal medicine, and healthcare cost reduction (Chang et al., 2026).

Current Challenges and Future Potential

Although much progress has been made in the development of WBSs, there are still some challenges that prevent their clinical adoption (Babu et al., 2024). The key challenges and their associated future potential are summarized in Table 2 below.

Table 2: *Challenges and Future Potential for the Clinical Implementation of Wearable Biosensors (Babu et al., 2024; Zhang, 2023)*

Area	Current Challenges	Future Potential
Wearable Device (User)	Data security, Data privacy, Device durability, Device robustness, Regulatory barriers.	Secure and encrypted wearable device design, Energy-efficient batteries, Implementation of internal calibration, Evaluation frameworks by regulatory agencies.
Data Processing, Storage and Cloud Computing	Data security, Lack of data standards, Data reliability, Data accuracy, Clinical Validity.	Implementation of Cybersecurity tools such as blockchain, Large-cohort RCT-based clinical validation, Data integration / Interoperable apps
Electronic Health Records (EHRs)	Lack of clarity on data quality, Interpretability, Accessibility of data insights in Electronic Health Record (HER).	Personalized reference ranges, Training of health care professional through Continuing Medical Education (CME), Data integration/Interoperable apps.
Clinical Implementation	Clarity on risks & benefits, Lack of education on correct usage & adherence.	Educational patients and clinicians, Recommendations linked to clinical evidence.
Measurements of Various Biomarkers	Existing technology is limited to measuring just a few biomarkers.	Creation of multianalyte biosensors and enhancement of non-invasive biofluid sampling techniques.
Accuracy and Reliability	Measurement accuracy is impacted by motion artifacts, environmental factors, and inter-subject variability.	Improve the accuracy and reliability of sensors, calibration techniques, and machine learning algorithms.
User Acceptance and Adoption	Worries regarding comfort, design, battery life, privacy, and usability.	Create devices that are user-friendly, easy to use, and have longer battery life and inform users of the benefits
Commercialization	Cost of manufacture, scalability problems, and regulatory considerations.	Cost-efficient manufacturing, large-scale manufacturing optimization, preclinical/ clinical validation, and regulatory strategy development

Conclusion

WBSs have revolutionized healthcare by making possible continuous, real-time, and non-invasive health monitoring of parameters that before could be measured only sporadically using laboratory tests. Flexibility of materials, nanomaterials, conductive composites, and further developments of these technologies increased the sensitivity, durability, biocompatibility, reliability, and comfort of wearables. In addition, development of signal acquisition and processing, noise reduction and calibration methods, and introduction of machine learning techniques improved signal accuracy, thus allowing better health monitoring. WBSs have found applications in clinical cardiology, diabetes treatment, respiratory disease monitoring, telemedicine, and drug administration monitoring. WBSs offer huge potential for providing a means of personalized and preventive medicine. At the same time, there are certain issues preventing the widespread use of the devices. These include data privacy and security, stability of the device, FDA clearance, scalable production, and clinical validation of the product. Further research should concentrate on creating multiplex biosensors, more biocompatible and anti-fouling materials, a validation protocol, and digital health ecosystem integration.

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