

Wearable Sensors for Physiological Monitoring: A Comprehensive Review

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Abstract. Wearable sensors are crucial for non-invasive and continuous health monitoring. The performance of these devices has been improved by recent advances in materials, device design and system integration. This review focuses on wearable sensors for physiological monitoring with special highlight on biophysical and biochemical sensing approaches. It discusses the ability of biochemical wearable sensors for biofluid biomarker analysis to provide molecular information to supplement physical measurements. Biophysical wearable sensors such as strain, pressure, temperature and bioelectrical sensors are also summarized. Their sensing mechanism and application in monitoring vital signs such as heart rate, respiratory rate, body temperature, blood oxygen saturation and cuffless blood pressure are discussed. The main challenges of wearable sensing including signal interference, interface stability, calibration and individual differences are also discussed. Finally, future directions of wearable sensor systems are highlighted with a focus on multimodal integration and translation towards clinically relevant and personalized health care applications.

Keywords: Wearable sensors, physiological monitoring, flexible materials, energy harvesting, healthcare

1. Introduction

Wearable biomedical devices enables continuously and non-invasively monitor physiological signals outside the clinical environment. These devices provide information about cardiovascular, respiratory, metabolic and behavioral states [1, 2]. Compared with traditional instruments, wearable systems allow repetitive and unobtrusive monitoring in daily life, which is conducive to early detection of physiological changes and personalized health assessment. Innovations in materials, electronics and processing technologies have further improved the comfort and reliability of wearable sensors [3].

Wearable sensing technologies can be broadly categorized into biophysical and biochemical fields (Figure 1). Biophysical sensors monitor vital signs, which includes heart rate, respiration, temperature, motion, and bioelectrical activity, through various signal transduction mechanisms [2]. Biochemical sensors analyze metabolites, electrolytes, and hormones in non-invasively collected biofluids, providing molecular-level information [4, 5]. These sensing methods together provide comprehensive information on the physiological status.

Although the development of wearable sensors is changing rapidly, there are still some challenges that limit long-term physiological monitoring in the real environment [2]. Biochemical sensing is often affected by problems such as sampling stability, low analyte concentrations and individual variability, while biophysical sensing is highly susceptible to motion artifacts, interference by the environment and instability of the skin-device interface. Practical factors such as power supply, mechanical comfort and wireless data transmission are also crucial in the design of wearable systems [6].

This article reviews the latest progress of biophysical and biochemical wearable sensors and classifies them according to the target physiological signals and sensing mechanisms. The article discusses representative applications to explain the function of each sensing method and compares their advantages and limitations. Finally, it focuses on the key challenges and future development directions to guide the development of a reliable wearable sensor system with clinical application value.

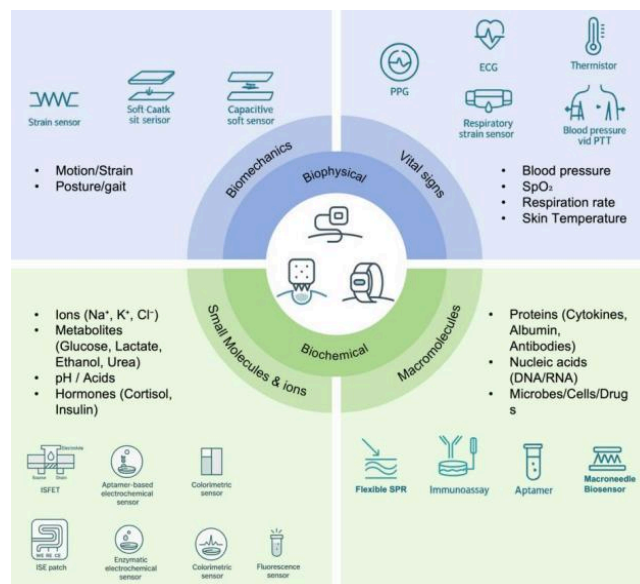


Figure 1. Overview of wearable sensing modalities, including biophysical and biochemical sensing approaches and their corresponding target signals and analytes

2. Biophysical sensors

Biophysical sensors convert mechanical, optical, thermal and bioelectrical signals from the human body into measurable electrical signal output. These devices are usually placed on the skin or built into textiles to track posture, exercise, and cardiovascular and respiratory functions in daily life [2, 3]. Here, we summarize representative modalities, including strain and pressure sensors, photoplethysmography (PPG), electrocardiography (ECG), thermistors, respiratory strain sensors, and blood pressure estimation via pulse transit time (PTT) [2]. Representative sensing principles of major biophysical wearable sensors are summarized in Figure 2.

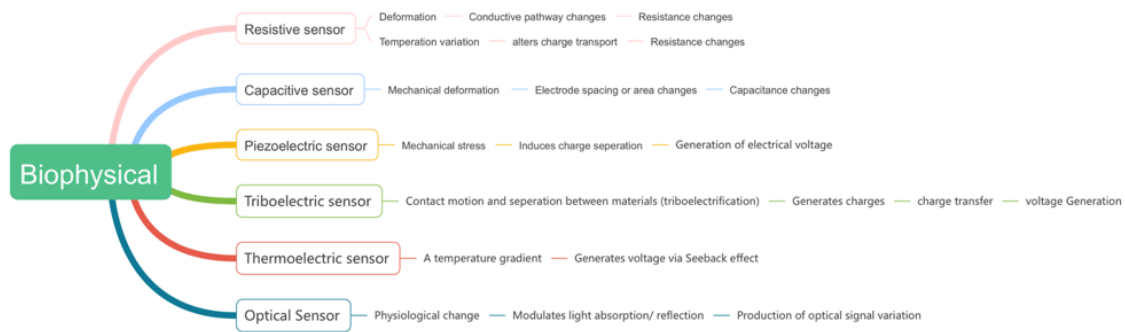


Figure 2. Sensing mechanisms of biophysical wearable sensors, including resistive, capacitive, piezoelectric, thermoelectric, and optical sensing principles

2.1. Mechanical signals

Mechanical wearable sensors transduce external forces and body deformations into electrical signals, enabling continuous monitoring of body motion in daily activities. Representative modalities include strain sensors for in-plane deformation and pressure sensors for normal forces [2, 3].

2.1.1. Deformation and strain sensors

The strain sensor captures the stretching, bending or compression of body parts by measuring the relative deformation of the base. When attached to joints or soft tissues, the strain sensor can record the joint angle, gait, posture, facial expression and subtle expansion of the chest during breathing [6]. A variety of stretchable conductors and composite materials, including serpentine metal wires, liquid metals, conductive polymers and nanomaterials, have been used in high deformation strain sensors [6-8].

Most highly ductility wearable strain sensors adopt a conversion mechanism based on resistance or capacitance [8]. Although both methods can adapt to large mechanical deformation, their sensing characteristics are completely different, so the application scenarios are also different.

Resistive strain sensors. Due to its simple reading and high strain sensitivity, resistance strain sensors are widely used to monitor large-scale joint movement, posture, gait and muscle deformation. Its working principle depends on deformable conductive materials or seepage networks embedded in an elastic substrate [8]. Mechanical deformation will change the geometry and connectivity of the conductive path, thus changing the resistance [2]. Using cracked films, low-dimensional materials or conductive gels, large deformation can be achieved while maintaining measurable electrical response [7].

The sensitivity of resistive strain sensors is usually quantified by the gauge factor (GF), which is defined as the relative change in resistance per unit strain [6, 7]. The gauge factor of traditional metal is low (~ 2), while nanomaterial sensors usually have higher sensitivity (~ 5 – 100), which can even exceed 1000 in crack-based or microstructure-engineered designs [8, 9]. However, these high sensitivities are often at the expense of linearity and repeatability.

Although resistance strain sensors are highly sensitive, they have some practical limitations. They are not suitable for quantitative and long-term physiological monitoring. The main challenge is the hysteresis caused by the viscoelastic effect of the flexible substrate and the irreversible changes in the conductive network during repeated deformation [6]. Also, signal drift over time, sensitivity to

temperature, humidity and environmental conditions, and the need for frequent calibration all reduce the reliability of the measurement [7, 10]. These issues are particularly important for applications that require continuous monitoring, such as respiratory tracking or joint motion analysis.

Capacitive strain sensors. Wearable systems with capacitive sensors have been used to monitor sole pressure, grip force, joint movement and subtle skin deformation. The capacitive strain sensor is based on a parallel plate or fork finger electrode configuration with electrodes separated by a deformable dielectric layer. Mechanical deformation will alter the electrode spacing or the effective dielectric constant which can be detected as changes in capacitance [6]. Large deformations are to be accommodated with the help of soft elastomers or dielectric materials based on foam or gel [7], which are used to maintain the mechanical strength.

Wearable systems with capacitive sensors are able to monitor plantar pressure, grip strength, joint movement, and subtle skin deformation. Capacitive strain sensors function based on a parallel plate or forked finger electrode structure with deformable dielectric layers separating the electrodes. Mechanical deformation causes changes in the electrode spacing or effective dielectric constant, resulting in capacitance changes [6]. Soft elastomers or dielectric materials based on foams or gels are usually used to accommodate larger deformations and maintain mechanical strength [7].

Capacitive strain sensors are less sensitive than resistive sensors, with gauge factors typically near 1 [6, 7, 11]. They do have several major benefits though, that make them especially attractive for wearable devices. One of the main advantages is that they can have almost linearity ($R^2 \approx 0.9999$) with small hysteresis, allowing for more repeatable and reliable measurements [7, 10, 11]. Moreover, they can keep stable performance in a wide strain range (up to 300%), which is appropriate for wearable applications with large deformation [10]. Furthermore, capacitive sensors usually have low hysteresis, as there are no irreversible changes in the conductive network. This leads to better repeatability in cyclic loading conditions.

Capacitive sensing also has the advantage of intrinsic long term stability [6, 7]. The sensing principle of the capacitive sensor is based on the geometric deformation [7, 12], which is less sensitive to signal drift and material fatigue. They are thus applicable to continuous physiological monitoring scenarios such as breathing monitoring and subtle body movement detection. Also, the calibration requirements of capacitive sensors are usually less than those of resistive sensors [6].

They are relatively insensitive and will limit their ability to detect very small deformations [2, 7, 12]. In addition, capacitor signals are easily affected by external electromagnetic interference and parasitic noise, making signal acquisition and circuit design more difficult [2, 6, 7]. The design is further complicated by the requirements of stable dielectric materials and precise structural fabrication.

Generally, resistance and capacitive strain sensors are two completely different sensing strategies, and each has its advantages and disadvantages. The sensitivity of the resistance sensor is higher, and its strain coefficient can reach more than 2 to 1000. The specific value depends on the material used [8, 9]. This characteristic enables it to detect tiny deformations efficiently. While, high sensitivity is usually accompanied by some limitations, such as hysteresis, signal drift and frequent calibration.

In contrast, the stretchability and sensitivity of capacitive strain sensors are lower, and their gauge factors are close to 1 [2, 6, 7, 11]. However, they have good linearity, minimal hysteresis and repeatability [7, 12]. These characteristics make capacitive sensors more suitable for applications that require stable and quantitative measurements over a long period of time.

Therefore, the choice between the two sensing methods should be based on the specific requirements of the intended application. A multimodal approach combining the advantages of both strategies is a promising option in many cases. Resistive sensors are better suited for high-sensitivity

detection of minute deformations; capacitive sensors are better suited for applications requiring long-term stability and quantitative monitoring.

2.1.2. Pressure and tactile sensors

Pressure sensors are another important type of biophysical wearable sensor that can respond to external mechanical stimuli, such as touch, compression or impact. Unlike strain sensors that mainly quantify specific directional deformations, pressure sensors are designed to detect the normal force perpendicular to the sensing surface. This characteristic makes them particularly suitable for monitoring tactile interaction and localized physiological pressures. In wearable systems, pressure sensing is usually realized through piezoresistive, capacitive and piezoelectric transduction mechanisms [3, 13].

Piezoresistive pressure sensors. Piezoresistive sensors measure the resistance change caused by the mechanical deformation of semiconductor materials. Although strain sensing and pressure sensing both use similar resistive transduction mechanisms, the difference between them lies in the dominant mechanical stimulus and structural design [13]. Due to their simple readout and high sensitivity, these sensors are widely used in the fields of plantar pressure mapping, tactile sensing and pulse waveform detection. However, piezoresistive pressure sensors are susceptible to hysteresis, temperature dependence and long-term drift under repeated loading [7].

Capacitive pressure sensors. Capacitive pressure sensors are usually composed of two conductive electrodes, which are separated by a compressible dielectric layer and supported by a substrate [14, 15]. When pressure and external force are applied, the distance between the electrodes changes, resulting in measurable changes in capacitance [16, 17]. Capacitive pressure sensors can achieve accurate pressure mapping, and the power consumption is relatively low. In particular, flexible wearable capacitive pressure sensors have shown great potential in the continuous detection of arterial pulse waveforms and beat-to-beat blood pressure monitoring [18]. However, their performance can be affected by parasitic capacitance and environmental interference and thus careful device design and calibration is required [19].

Piezoelectric pressure sensors. Piezoelectric sensors employ the piezoelectric effect to measure the electrical potential generated by materials under mechanical stress. Piezoelectric films are usually fabricated between two electrodes. Mechanical deformation causes an accumulation of charges on the two electrodes, which results in measurable changes in the voltage signal [20]. These sensors are particularly suitable for dynamic pressure detection and transient mechanical events such as vibrations and pulse waves. However, piezoelectric sensors are not suitable for static pressure measurements since charges leak off with time [18].

Generally, pressure sensors and tactile sensors can be combined with strain sensors to sense contact information and normal forces jointly. Despite the advantages of each sensing mechanism, issues such as signal drift, sensitivity to the environment, and mechanical durability remain significant challenges for the long-term deployment of wearable devices, especially in practical application environments. Therefore, the choice of an appropriate sensing mechanism should depend on the specific requirements of the application such as sensitivity, stability, stretchability and working conditions.

2.2. Thermal signals

Temperature sensors are one of the important types of wearable biophysical sensors that allow continuous measurement of skin and body temperature. Temperature is an important physiological

parameter that provides important information about thermoregulation, metabolic activity and early signs of infection or inflammation. Wearable systems use temperature sensing based on the changes in electrical properties of temperature-sensitive materials. Resistive, thermoelectric and semiconductor based sensing mechanisms are commonly used [1, 3].

2.2.1. Resistive temperature sensors

Thermistors are temperature sensors that change their electrical resistance predictably with the temperature. Among these, the negative temperature coefficient (NTC) thermistors, whose resistance drops with increasing temperature, are widely applied in wearable devices because of their high sensitivity and low cost [1, 3]. Wearable thermistors in direct contact with the skin or near the body surface can be used to continuously monitor skin temperature for applications such as fever detection, circadian rhythms, metabolic rate, and ovulation cycles [2, 5]. However, skin temperature can be different from core body temperature, depending on environmental conditions [21].

Advanced wearable systems typically combine thermal insulation layers, optimized sensor placement and multi-site temperature measurements with algorithmic compensation methods to better approximate core body temperature [22]. These strategies are helpful to improve the measurement accuracy and stability while to keep the flexibility and comfort required for long-term wearable applications.

2.2.2. Thermoelectric temperature sensors

Thermoelectric temperature sensors work based on the Seebeck effect, and the temperature gradients on two different conductive materials generate an electrical voltage [23]. In wearable applications, thermoelectric sensors can enable self-powered temperature sensing without external power supply and reduce system complexity [1].

These sensors are attractive for long-term physiological monitoring because they can perform temperature sensing and energy harvesting at the same time [5]. However, the actual performance is usually limited by a small and variable temperature gradient in a wearable environment [1, 3].

In addition to material and device-level temperature sensing strategies, the epidermal wireless system can also achieve battery-free and unobtrusive thermal monitoring [24]. For example, the RFID-based epidermal temperature sensor integrates a flexible antenna with a thermal IC sensor to achieve a miniaturized and skin-mounted platform that can carry out accurate temperature monitoring under realistic operating conditions [25].

Although resistive temperature sensors have high sensitivity and simplicity, their accuracy is usually limited by environmental interference such as airflow and sweat evaporation. In contrast, thermoelectric sensors provide self-powered operation but are limited by small temperature gradients that can be used under wearable conditions, which limits the reliability of the signal.

In addition, environmental temperature, airflow, fluctuations in sweat evaporation and changes in sensor placement will significantly affect the measurement accuracy. This makes it challenging to reliably estimate the core body temperature in practical applications.

2.3. Optical signals

Photoplethysmography (PPG) Photoplethysmography (PPG) is an optical sensing technique that measures changes in blood volume within the microvasculature by detecting variations in light absorption associated with the cardiac cycle [25]. In a typical PPG system, the skin is illuminated by

a light source, usually by a green or infrared LED, and the photodetector measures the intensity of transmitted or reflected light [26, 27]. The periodic variation of the detected signal corresponds to pulsatile blood flow and leads to a waveform synchronized with cardiac pulse [25].

Wearable PPG has been widely used in wristbands, watches and rings to continuously monitor heart rate and heart rate variability [25]. By detecting the changes in blood volume via absorption of green or infrared light, PPG can provide a high-fidelity waveform synchronized to the cardiac cycle [26, 27]. In addition to HR and SpO₂, its clinical applications have extended to hemodynamic assessment, including cuffless blood pressure estimation based on PTT [27].

In terms of performance, wearable PPG systems are able to provide a relatively accurate estimation of the heart rate in resting conditions but the accuracy tends to decrease during physical activity. Systematic evaluation studies have demonstrated that the measurement errors are increased under motion conditions, showing the significant effect of motion artifacts on signal quality [28, 29].

For example, Bent et al. [28] reported that consumer-grade wearable devices achieved a mean absolute error (MAE) of 7.2 ± 5.4 bpm at rest, whereas research-grade devices showed an MAE of 13.9 ± 7.8 bpm ($p < 0.0125$). During physical activity, the MAE increased to 10.2 ± 7.5 bpm and 15.9 ± 8.1 bpm, respectively. These results indicate a significant drop in performance in the presence of motion. They also indicate that the accuracy of wearable PPG may vary considerably across devices and use cases, even in controlled settings..

However, wearable PPG systems are very sensitive to motion artifacts, probe position, probe contact force and ambient light interference [25, 26]. Furthermore, low peripheral perfusion and increased skin pigmentation can affect measurement accuracy [28]. To reduce these effects, motion-robust signal processing algorithms, multi-site sensing strategies, and sensor fusion approaches are often employed to improve the signal quality and reliability [30, 31].

In conclusion, PPG is still very attractive for compact and continuous cardiovascular monitoring. But its real-world performance is still affected by device design and physiological variability, suggesting the need for better calibration and robustness for clinical-level applications.

2.4. Bioelectrical signals

Wearable bioelectric signal monitoring can directly monitor electrophysiological pathways and support a wide range of applications from fitness tracking to early cardiovascular disease detection [32]. Heart rate and respiratory rate are two of the most commonly monitored vital signs in wearable health care systems [1-3]. The parameters can be obtained by mechanical or optical methods (e.g. PPG) [7, 25] but direct bioelectrical measurement remains the clinically important standard.

Electrocardiography (ECG) The Electrocardiography (ECG) sensor measures the electrical activity of the heart, which results in the difference in the skin potential [33]. In traditional systems gel electrodes are used whereas in wearable platforms more and more dry metal electrodes, conductive textiles and printed electrodes are used [34]. Smart watches with integrated patches, chest straps and single-lead electrodes are available to gather information about heart rhythm.

Traditionally, from the point of view of system design, wearable wireless electrocardiogram devices are usually fitted with integrated systems, such as electrodes, analog front end (AFE), data acquisition (DAQ) modules, digital signal processing (DSP) units, wireless communication interfaces and power management components [35].

ECG provides detailed information about arrhythmia, conduction abnormalities and heart rate variability, making it the gold standard of electrophysiological cardiac monitoring [36]. Electrocardiograms are less affected by the state of peripheral blood vessels than PPG and require good skin-electrode contact [25, 33]. Skin irritation and dryness of electrodes and impedance

changes due to movement will decrease the quality of the signal in long-term wearing [37]. These factors will affect the stability of the signal in real wearable applications, which will limit the reliability of the continuous monitoring.

2.5. Derived physiological parameters

2.5.1. Respiratory rate sensors

Respiratory rate is an important physiological parameter reflecting pulmonary function, metabolic demand and autonomic regulation [38]. In wearable systems, the respiratory rate is usually estimated from biophysical signals rather than directly measured. One of the common ways is respiratory-induced modulation of photoplethysmography (PPG) [25]. Intrathoracic pressure, venous return and autonomic activity are affected by breathing, causing variations in signal amplitude, baseline and frequency [25, 38]. These modulations can be extracted from the signal by signal processing methods such as band-pass filtering and spectral analysis, so that respiratory rate can be estimated continuously [39].

Besides the PPG-based methods, the respiratory rate can also be derived from electrocardiogram (ECG) signals through respiratory sinus arrhythmia, where heart rate increases during inspiration and decreases during expiration [39, 40]. In addition, inertial and deformation-based sensors like accelerometers, gyroscopes and capacitive textile sensors embedded into wearable devices are able to record chest or abdominal movements linked to breathing and thus offer an alternative mechanical sensing pathway [41]. These techniques enable to use existing sensors on many wearable platforms for respiratory monitoring.

Indirect respiratory rate estimation is highly practical but inherently flawed, because it relies on secondary signals rather than actual airflow, physical activity, posture changes, and altered breathing patterns easily trigger major errors [38]. This vulnerability is common across wearable tech. For instance, impedance pneumography shows wide Limits of Agreement (LoAs)—roughly -9.9 to 7.5 bpm and -11.1 to 11.9 bpm depending on the conditions—with performance dropping sharply during movement [39].

In a clinical setting, these inaccuracies lead to false alarms, which drain system resources and reduce user trust. Ultimately, while wearable respiratory monitoring has great promise, delivering reliable data in complex, real-world environments remains challenging.

2.5.2. Blood pressure sensors pulse transit time (PTT) approach

Pulse transit time (PTT) is one of the most common methods for cuffless blood pressure estimation and is defined as the time delay of the pulse wave propagation between two measurement sites [42]. The Moens–Korteweg and Hughes equations essentially account for the PTT. These equations relate pulse wave velocity to properties of the arterial wall such as elastic modulus and vessel geometry [43, 44]. However, the Moens-Korteweg formulation is based on some simplifying assumptions, such as the assumption of constant arterial diameter and ignoring its dynamic variation during the cardiac cycle [45]. Actually, the arterial diameter changes with pulsatile pressure and vascular tone, making it nonlinear and causing inaccuracies in PTT-based blood pressure estimation [45].

Its integration into ECG-PPG wearables provides a cuffless alternative for BP estimation, but the clinical accuracy is severely degraded by the Pre-Ejection Period (PEP) [45, 46]. PEP is modulated by myocardial contractility and not by arterial pressure, it is a non-negligible source of noise on the results. Unlike conventional cuff-based methods, PTT-based approaches are attractive for wearable

applications as they provide continuous and unobtrusive monitoring without the need for bulky inflatable cuffs. PTT-based systems have shown promising performance under relatively stable physiological conditions such as during sleep. For example, one previous study showed the difference between PTT-estimated systolic blood pressure (SBP) and reference measurements was 4.8 ± 4.3 mmHg and a high negative correlation in the night-time monitoring [46].

Physiological and operational limitations affect the accuracy of PTT based estimation. In the absence of environmental disturbances and physiological variability, PTT has been demonstrated to estimate the blood pressure with reasonable accuracy. But these results are often inapplicable to dynamic environments where there are variations in vasomotor tone and hydrostatic pressure predominate. To overcome the limitation of PEP, alternative sensing modalities have been investigated to track the timing of aortic valve opening. Mechanical cardiac events can be measured by techniques such as impedance cardiography (ICG) and seismocardiography (SCG) and thus enable the separation of the PEP from the vascular transit time [44, 47]. These methods aim to provide a more physiologically relevant measurement of pulse propagation.

The relationship of PTT to blood pressure is also highly subject-specific and often non-linear, requiring individual calibration that can drift over time. Thus, correlation coefficients between SBP and PTT have been reported to vary widely between individuals, and to range from approximately -0.4 to -0.97 even under relatively stable nighttime conditions [46]. This large variability between subject implies the complexity of the underlying physiological influences such as autonomic regulation, vascular tone and hormonal fluctuations.

The PTT estimation is also sensitive to the signal quality and feature extraction. Timing errors of the ECG R-peak or of the fiducial points of the PPG waveform introduce significant timing uncertainty, often larger than 10% in traditional algorithms [48, 49]. Moreover, the different definitions of PTT such as the foot or peak of the PPG waveform can cause variability in robustness and accuracy [27, 44]. In wearable settings, however, signal quality is further degraded by motion artifacts, sensor displacement, and environmental interference [27, 44, 50].

Overall, PTT provides a promising platform for cuffless and continuous blood pressure monitoring, but is limited by calibration dependency, physiological variability and sensitivity to measurement conditions. To address these challenges, modelling, multimodal sensing and validation in real-world conditions need to be improved.

3. Biochemical sensors

Wearable biochemical sensors allow analysis of biofluids collected through non-invasive means such as sweat, saliva, tears and interstitial fluid (ISF) for metabolites, electrolytes and other biomarkers [1, 3, 51]. These biofluids carry information about both systemic and local physiological states [52]. Detected analytes include ions, metabolites, organic acids, hormones and proteins [4, 53]. Biochemical sensors are thus appropriate for sampling outside of the clinical environment, enabling continuous physiologic monitoring. Figure 3 summarizes representative sensing strategies adopted in wearable biochemical sensors.

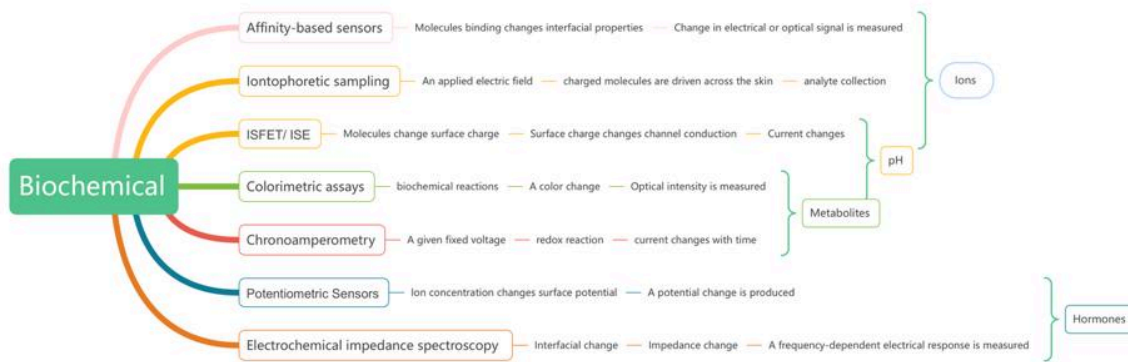


Figure 3. Sensing strategies for wearable biochemical sensors, including electrochemical, colorimetric, and affinity-based detection approaches

3.1. Biofluid sources

Several biofluids have been examined as sampling media for wearable biochemical sensors. Sweat is one of the most accessible biofluids and is easily collected in a non-invasive manner [4]. It includes a wide spectrum of biomarkers related to systemic and local physiological status. Sweat can be collected passively or induced by thermal heating, chemical stimulation, electrical induction or psychological stress [2, 4, 54]. Saliva contains proteins, ions, hormones and several organic compounds that offer valuable insights into oral and systemic health [55]. Another valuable source of biofluids for monitoring electrolytes, glucose and protein biomarkers such as mucins is tears. One major advantage is their relatively stable composition [56]. Metabolites, hormones, and proteins involved in systemic physiology and skin conditions are present in the interstitial fluid (ISF) that surrounds cells [57]. Different biofluids have their own advantages and limitations in terms of analyte concentration, secretion rate and collection strategy [58].

3.2. Ion sensors

Electrolytes, such as sodium (Na^+), potassium (K^+), and chloride (Cl^-), are markers for hydration status, electrolyte balance, and related disorders [51]. In wearable biochemical sensors, the concentrations of these ions in sweat, saliva and interstitial fluid (ISF) are routinely measured. Electrochemical ion selective electrodes (ISEs), a kind of electrochemical potentiometric sensor, are among the most widely used sensing strategies due to their high selectivity. ISEs determine the concentration of electrolytes by measuring the potential difference between a reference electrode and a sensing electrode [4].

From a clinical point of view, ion monitoring is highly relevant for applications such as dehydration assessment, cystic fibrosis screening and electrolyte imbalance detection in athletes or critically ill patients [49, 59]. However, they have not been widely used in the clinical setting, despite their good analytical performance. This is mainly because of a high inter-individual variability in sweat composition, dependence on sweat rate and sensitivity to contamination or evaporation effects distorting measured ion concentrations [60]. Also, the electrolyte levels in sweat do not always correlate directly with blood electrolyte levels, making them less reliable for clinical decision making [60, 61]. Thus, today's wearable ion sensors are better suited for trend monitoring and wellness applications, rather than for reliable diagnostic tools.

3.3. Metabolite sensors

Metabolites are small molecules necessary for energy production and physiological regulation. Common metabolites detected by wearable biochemical sensors include glucose, lactate, ethanol, and urea. Electrical and colourimetric sensors integrated into microfluidic devices are both commonly used to monitor metabolite concentrations [53].

Metabolite-sensing strategies can be broadly categorized into catalyst-based and bioaffinity-based sensors. Electrochemical transduction of metabolites is often achieved through chronoamperometry, particularly for enzyme-based sensing [53]. These approaches enable applications such as non-invasive glucose monitoring for diabetes management. However, sweat glucose concentrations are typically in the micromolar range, one to two orders of magnitude lower than blood levels [62], posing challenges for accurate detection and limiting the reliability of non-invasive metabolite sensing.

Metabolite sensing, particularly glucose monitoring, is one of the most clinically important applications of wearable biochemical sensors. Continuous glucose monitoring (CGM) systems are already widely used in diabetes care [63, 64]. Other metabolites also have clinical relevance. Lactate monitoring may help assess tissue hypoxia and sepsis, whereas ethanol sensing can be used for tracking alcohol consumption [64, 65].

There are still a number of challenges facing non-invasive wearable metabolite sensing. Sweat or ISF glucose concentrations are often lower than blood glucose levels and can have a detectable time lag [4, 66]. Calibration and modelling techniques can compensate for some of these effects, but accuracy is still a concern. Enzyme-based sensors also suffer from poor stability, temperature sensitivity and biofouling, which can cause gradual performance degradation during long-term use [67].

While clinical CGM systems have demonstrated excellent performance, fully non-invasive sensing from alternative biofluids poses challenges to replicate such reliability. Limitations for the use of these systems as reliable clinical diagnostic tools include low analyte concentrations, physiological delays and poor correlations with blood measurements.

3.4. pH sensors

pH is a significant physiological parameter as it affects many biological and chemical processes in the body [68]. Many wearable pH sensors using electrochemical methods have been developed, such as ion-selective electrodes (ISEs) for H_3O^+ detection and ion-sensitive field-effect transistors (ISFETs) [69, 70]. Colorimetric sensor arrays combined with microfluidic devices have been developed for pH measurements [53]. However, differences in biofluid secretion rates continue to be a significant source of measurement uncertainty [58].

pH monitoring might be helpful in the management of wounds, the assessment of skin health and management of metabolic disorders. pH changes are often linked to infection, inflammation, and impaired tissue repair [71, 72]. For example, pH sensing can be used to monitor the wound healing process, since chronic wounds are usually at a higher pH [71].

There are several factors that can influence the accuracy of wearable pH sensors. The measured results can be affected by differences in the secretion rates of biofluids, exposure to the surrounding environment, and sensor drift in long-term use [58]. Local pH values may differ from the overall acid–base status in the body. As such, measurements at any one site do not necessarily reflect systemic physiological states. Therefore, current wearable pH sensors are better suited for localized monitoring applications than for the evaluation of the acid–base balance of the entire body.

3.5. Hormone sensors

Hormones are key biochemical regulators, mediating stress response, metabolism, and endocrine function. Hormone levels change with physiological state and therefore can be useful in providing information about stress, metabolic activity and hormonal disorders. Cortisol is one of the most studied targets in wearable biochemical sensing owing to its association with stress, depression, and anxiety [73]. Sweat, saliva and tears have all been explored as potential sources for cortisol monitoring. Hormone sensing is typically done with bioaffinity based sensors that rely on specific molecular binding or conformational changes [53, 73]. Electrochemical impedance spectroscopy (EIS) is commonly used to assess the binding of cortisol on functionalized electrode surfaces. Researchers have also shown insulin detection in interstitial fluid (ISF) with microneedle-based sensors. Insulin monitoring in ISF is more challenging than monitoring small molecules because of the much lower concentrations of insulin. Vascular permeability also restricts its transport from blood vessels to the ISF. This still makes accurate ISF insulin measurement difficult. Blood tests are therefore the gold standard for insulin testing, and ISF measurements are usually regarded as complementary information [53].

The hormone sensing could be used for stress monitoring, assessment of circadian rhythm and management of endocrine disorders. For example, continuous cortisol monitoring can be used to track long-term stress and mental health conditions [74]. However, despite this potential, there are still several technical hurdles to overcome. Their accurate detection in non-invasive biofluids is often challenging due to their very low concentrations. Circadian rhythms, environmental conditions, and individual differences may also influence measured levels [75]. Additional deterioration of sensor performance can be also caused by biofouling, limited specificity and stability issues during long-term operation. These factors are still the major limitations to the practical use of wearable hormone sensors in clinic.

A comparison of major wearable sensing modalities, including their advantages, limitations, and clinical readiness, is summarized in Table 1.

Table 1. Comparison of wearable sensing modalities in terms of sensing targets, advantages, limitations, and clinical readiness

Sensing Modality	Advantages	Limitations	Clinical Readiness
Strain sensor	High sensitivity to deformation; suitable for motion tracking	Signal drift; hysteresis; calibration required	Moderate (rehabilitation, motion monitoring)
Pressure sensor	Contact and normal forces detection; simple structure	Nonlinearity; durability issues under repeated loading	Moderate (gait, tactile sensing)
Thermal sensor	Simple continuous monitoring; useful for thermoregulation	Environmental influence; weak correlation with core temperature	Moderate (trend monitoring)
PPG	Non-invasive; HR and SpO ₂ monitoring	Motion artifacts; sensitivity to placement and skin conditions	High (widely used in wearables)
ECG	Gold standard for cardiac monitoring; high accuracy	Requirement for good contact; long-term discomfort	High (clinical and wearable devices)

Table 1. (continued)

PTT (BP estimation)	Cuffless and continuous blood pressure monitoring	Calibration dependency; PEP interference; physiological variability	Limited (research-stage, not yet reliable clinically)
Ion sensing	High selectivity; real-time electrolyte monitoring	Sweat variability; contamination; weak correlation with blood	Limited (mainly hydration & screening)
pH sensing	Simple detection; useful for local conditions	Drift; environmental sensitivity; localized only	Limited (wound monitoring)
Metabolite Sensing	Metabolic monitoring; CGM well-established	Low concentration; time lag; stability issues	Mixed (CGM established; non-invasive still emerging)
Hormone sensing	Insight into stress and endocrine function	Very low concentration; complex detection; slow response	Emerging (research-stage)

4. Outlook and discussion

In recent years, wearable sensor technology has developed rapidly, realizing continuous and non-invasive monitoring of biochemical and biophysical signals [2, 5]. With the continuous progress of sensing materials, device design and system integration technology, wearable sensors are developing from simple health tracking to more clinical applications.

Multimodal sensing is one of the important directions of future development [17, 32]. The single sensing mode is usually susceptible to motion artifacts and environmental interference, and the combination of mechanical, thermal, optical and electrical signals can improve physiological correlation. The multi-modal wearable system also supports cross-verification between signals, so as to evaluate vital signs more reliably [17].

But long-term wearability remains a challenge for wearable sensors. Daily movement can disrupt skin contact, while factors such as comfort, breathability, and user compliance can reduce signal quality. The use of flexible materials, textile-based designs, and stretchable electronics may help improve performance and comfort.

Many physiological parameters, including blood pressure and respiratory rate, are estimated indirectly and require calibration [39, 42]. Their accuracy can vary between individuals and over time. Future systems will need more adaptive algorithms to improve accuracy while maintaining low power consumption and data security [30].

Despite the good development momentum, the clinical application is still very low. The current research is inconsistent in the verification method, and few devices have been tested under real long-term conditions. To bridge this gap, standardized testing, approval from regulators and integration into existing health care systems are needed.

Ultimately, while technical and clinical challenges remain, steady breakthroughs in materials science, device engineering, and data analytics will continue to push wearable sensors deeper into both clinical medicine and daily health management.

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