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Review

Emerging intelligent wearable devices for cardiovascular health monitoring

Yiqian Wang [a,b,c], Yang Zou [a,b,*], Zhou Li [b,c,d,**]

[a] School of Medical Technology, Beijing Institute of Technology, Beijing 100081, China
[b] Beijing Institute of Nanoenergy and Nanosystems, Chinese Academy of Sciences, Beijing 101400, China
[c] School of Physical Science & Technology, Guangxi University, Nanning 530004, China
[d] School of Nanoscience and Engineering, University of Chinese Academy of Sciences, Beijing 100049, China

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ABSTRACT

Cardiovascular diseases have long posed a significant threat to human health. Wearable devices are increasingly vital in cardiovascular health monitoring, disease screening, and early warning because of their non-invasiveness, real-time data provision and continuous monitoring capability. The collection, processing, and analysis of data in cardiovascular health monitoring involve numerous repetitive and standardized tasks, where artificial intelligence (AI) technology plays a pivotal role. AI is particularly effective in handling large volumes of data, thus enhancing the diagnostic and predictive capabilities of wearable devices. This review summarizes essential indicators for assessing cardiovascular health and provides a comprehensive introduction to commonly used non-invasive monitoring methods, including pulse pressure, photoplethysmography, electrocardiogram, bioimpedance analysis, seismocardiography/ ballistocardiography, and ultrasonography. Additionally, some impressive advances in wearable cardiovascular health monitoring technologies are reviewed and their integration with AI is highlighted, demonstrating typical application cases from recent years. Finally, the review discusses the current challenges of integrating AI into wearable devices for cardiovascular health monitoring, focusing on aspects from device design, algorithm optimization, comfort, reliability, and security. With the seamless integration of AI and wearable devices, a new generation of wearable intelligent devices promises to revolutionize the monitoring, prevention and management strategies of cardiovascular diseases.

Introduction

Cardiovascular diseases (CVDs) are one of the most common causes of death worldwide, accounting for one-third of global deaths and ranking first among all diseases[1–3]. Moreover, the cost of treating CVDs is prohibitively high. According to the World Heart Federation, the total cost of treating CVDs worldwide will reach an astonishing $1044 billion by 2030[4]. CVDs are a series of heart and vascular diseases, mainly including hypertension, atherosclerosis, coronary heart disease, and myocardial infarction, among others. Early detection and intervention, along with regular risk screening for cardiovascular conditions, can significantly reduce the incidence of CVDs[5,6].

Currently, blood pressure (BP), electrocardiogram (ECG) and ultrasound are the primary methods for noninvasive CVDs screening[7]. BP and ECG are both crucial for evaluating cardiovascular health, but they focus on different aspects [8,9]. BP measures the state of circulation, while ECG assesses the heart's electrophysiological state. Continuous ECG monitoring aids in identifying heart-related conditions and provides alerts for specific diseases, such as latent arrhythmias. Ultrasonography offers visual information about the heart's structure and function. Clinical instruments for cardiovascular assessment are often cumbersome, stationary, and reliant on medical professionals. They also involve high costs, lengthy testing times, and the risk of misdiagnosis or missed diagnosis. In recent years, there has been an increasing focus on the potential of wearable devices to monitor and prevent CVDs. The emergence of wearable technology can provide round-the-clock health monitoring without affecting users' daily lives. Highly integrated functions allow users to view various cardiovascular-related physiological indicators. Long-term monitoring data can provide doctors with additional daily insights for diagnosis. Concomitant with the rapid evolution of sensing technologies, and propelled by advancements in artificial intelligence (AI), big data analytics, cloud computing, and 5 G telecommunications, state-of-the-art intelligent wearable devices have significantly enhanced in both accuracy and efficiency. These devices

* Corresponding author at: School of Medical Technology, Beijing Institute of Technology, Beijing 100081, China.
** Corresponding author at: Beijing Institute of Nanoenergy and Nanosystems, Chinese Academy of Sciences, Beijing 101400, China.
E-mail addresses: zouyang@bit.edu.cn (Y. Zou), zli@binn.cas.cn (Z. Li).

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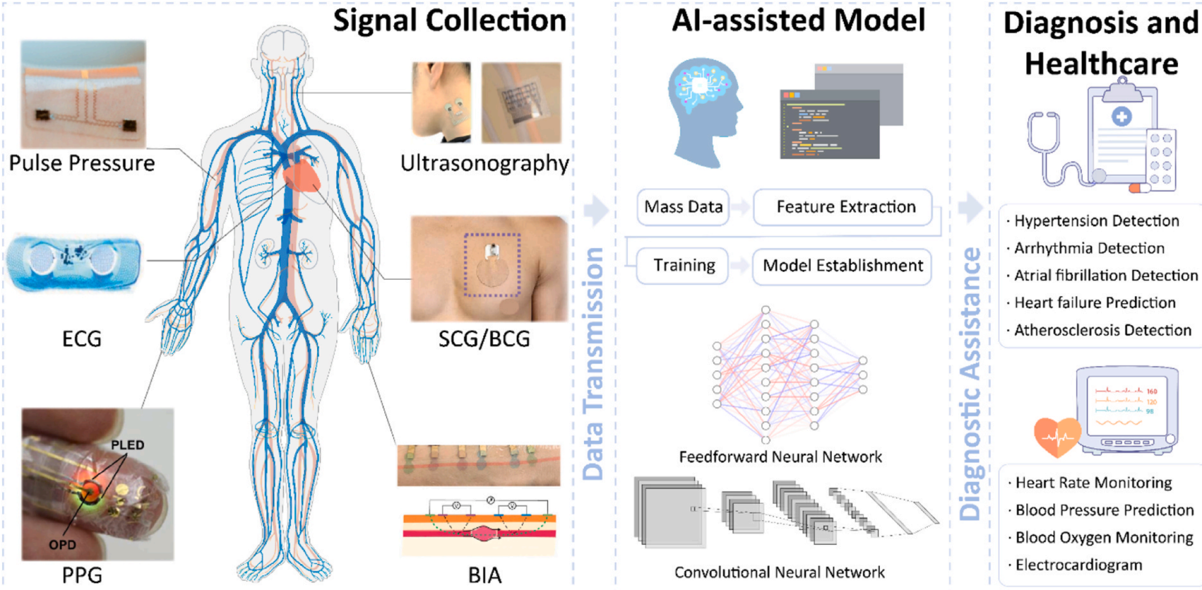

Fig. 1. Schematic diagram of cardiovascular health monitoring and disease assisted diagnosis process combining emerging wearable devices and AI. Collect physiological information such as pulse waves, ultrasound, and ECG from the human body, and then transmit it to AI diagnostic models, ultimately achieving the goals of disease diagnosis and health monitoring. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[153,154,162,167]. Reproduced with permission[96], Copyright 2018, Springer Nature[50]. Reproduced with permission, Copyright 2018, Springer Nature.

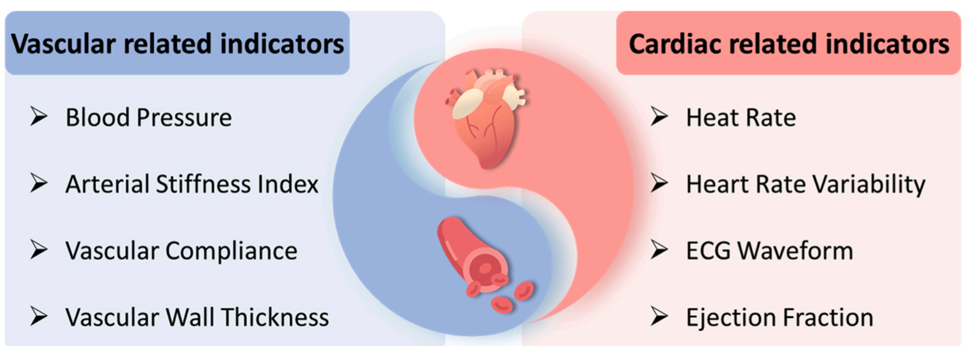

Fig. 2. Important indicators of cardiovascular health monitoring.

offer personally tailored auxiliary diagnostic and therapeutic strategies, granting users access to superior-quality medical and healthcare services. The advent of the Internet of Medical Things powered by intelligent wearable devices represents a transformative approach to the monitoring and management of CVDs. By facilitating prevention, continuous monitoring, and comprehensive management, it holds the promise of significantly reducing both the incidence and mortality rates of CVDs.

This review first examines key metrics used in clinical settings for cardiovascular health monitoring, covering both cardiac and vascular perspectives. It then presents the features and principles of six popular wearable cardiovascular health monitoring technologies: pulse pressure, photoplethysmography (PPG), ECG, bioimpedance analysis (BIA), seismocardiography (SCG) / ballistocardiography (BCG) and ultrasonography. Then, in light of the rapid advancement of AI technology, we conducted a comprehensive comparison between traditional clinical cardiovascular health assessment methods and the emerging auxiliary diagnostic technology augmented by AI. Furthermore, around the six cardiovascular health monitoring methods mentioned above, the latest representative research progresses on emerging wearable technologies integrated with AI aimed at preventing and assisting in diagnosing CVDs were introduced. Finally, we summarized and looked forward to the future development of intelligent wearable devices for monitoring cardiovascular health status from device design, algorithm optimization, comfort and stability, and safety. Integrating advanced sensing technologies and machine learning in wearable devices is expected to revolutionize CVDs prevention and management, ultimately reducing the disease burden on individuals and the global healthcare system (Fig. 1).

Vital indicators of cardiovascular health monitoring

To efficiently monitor and assess cardiovascular health, it is essential to understand the key indicators that describe and evaluate the state of cardiovascular conditions. Here, we roughly divide these indicators into two categories, as shown in Fig. 2. One describes the cardiac state, including heart rate[10], heart rate variability[11], ECG waveforms [12], and ejection fraction[13]. These indicators mainly describe the electrophysiological, functional, and dynamic states of the heart. Another type of indicator that describes vascular status, such as BP[12,14], arterial stiffness index[15], vascular compliance[16] and vascular wall thickness[17,18] serve to characterize the oxygen transport capacity of the vessels, the blood flow conditions within the vessels, as well as the pliability and stiffness of the vascular walls.

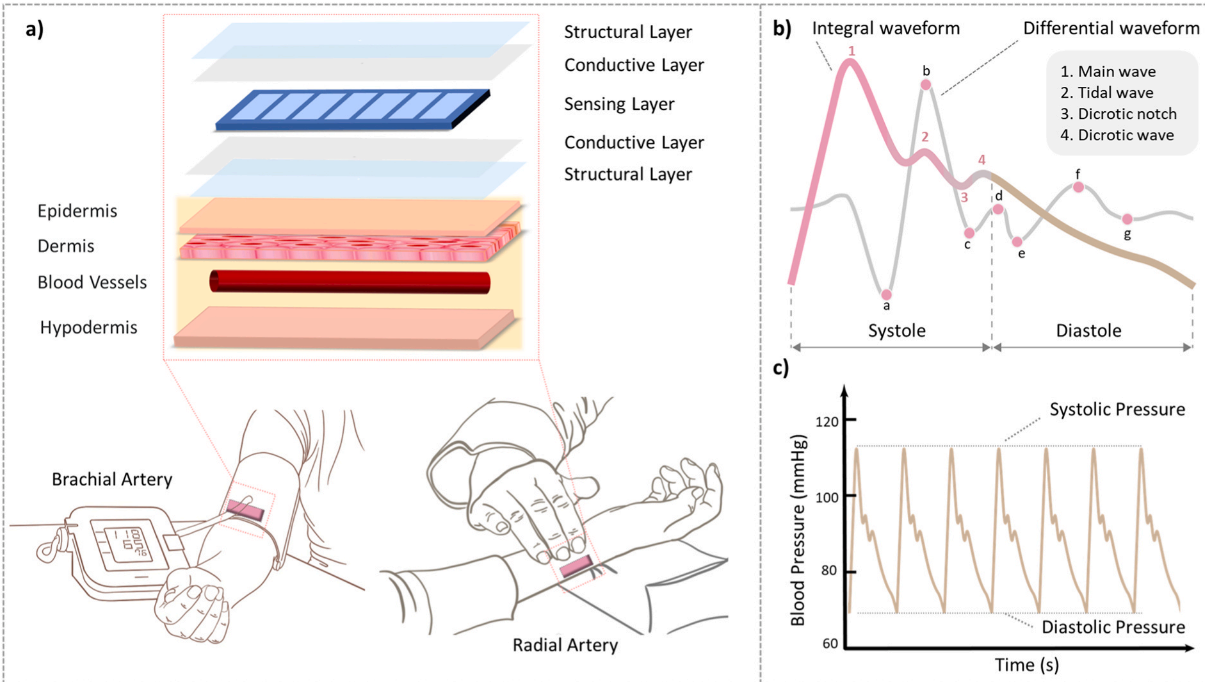

Fig. 3. Principles, detection methods and signal characterization of pulse pressure sensors. a) Schematic diagram of pulse monitoring and pressure sensor structure, b) Pulse waves in integral and differential forms, c) Pulse waves in relation to BP, systolic and diastolic pressures.

The heart and vessels share a close, interdependent relationship and together comprise the cardiovascular system[19,20]. The heart determines the flow and pressure of blood, acting as a pump to deliver blood throughout the body[21]. The state of the vessels—such as their width, elasticity, and resistance—affects blood flow. Conversely, the heart and vessels influence each other. For example, the pumping power of the heart towards blood (cardiac output) directly affects BP. On the contrary, if vascular resistance increases, the heart needs more force to pump blood, which may result in a faster heart rate. In summary, the physiological indicators related to the heart and vessels are closely interconnected. Understanding the relationship between these two parts is crucial for the assessment and monitoring of cardiovascular health.

When monitoring cardiovascular health, each indicator has its unique significance and value. Specifically, heart rate refers to the number of times the heart beats per minute, which can reflect the blood supply to the body and the health status of the heart. In healthy adults, the resting heart rate typically ranges from 60 to 100 beats per minute. A heart rate exceeding 100 beats per minute is classified as tachycardia, whereas one that falls below 60 beats per minute is termed bradycardia. Persistent tachycardia or bradycardia may indicate underlying cardiac abnormalities such as myocarditis or sick sinus syndrome, among other conditions[22–24]. Heart rate variability refers to the change in the interval time between heartbeats, reflecting the stability of the autonomic nervous system of the heart, which is an important indicator for evaluating heart function. Ejection fraction is a parameter used to assess the heart's pumping efficiency. Typically, a normal ejection fraction ranges from 55 % to 70 %. ECG is one of the most commonly used indicators for cardiac assessment in clinical settings. It is highly valued for its ability to provide essential information about cardiac electrical activity quickly, simply, and non-invasively. The ECG is extremely useful for detecting and diagnosing various cardiac conditions, including arrhythmias[25–28] and myocardial infarctions[29]. An ejection fraction below the normal range is generally considered an indicator of reduced cardiac pumping function. An ejection fraction below 40 % is often regarded as one of the criteria for heart failure[30,31].

In assessing vascular health, both systolic and diastolic BP, are critical indicators. Elevated BP can increase heart burden and risk of coronary heart disease, while low BP may cause dizziness and chest tightness[32–34]. The arterial stiffness index, assessed by pulse wave velocity, reflects the elasticity or stiffness of the arteries and is an important indicator of arterial status[15]. Vascular compliance, defined as the ability of blood vessels to dilate and contract, is assessed by BP waveforms and reflects the health of blood vessels[16]. Its decrease is commonly observed in atherosclerosis. Increased vessel wall thickness, which can be assessed by imaging techniques such as ultrasound, is an early sign of atherosclerosis[17,18].

The utilization of these indicators enables efficient evaluation of cardiovascular health, facilitating the detection and prevention of CVDs. To collect and utilize these indicators more effectively, a range of sensing technologies and devices based on various principles has been developed, including but not limited to pulse pressure, PPG, ECG, BIA, BCG/SCG, and ultrasonography[35]. These advancements enable a thorough cardiovascular health assessment, offering diverse insights, enhancing diagnostic accuracy, and improving intervention timeliness.

Sensing technologies for cardiovascular health monitoring

Various methodologies currently collect cardiovascular health indicators using sensors operating on distinct principles. These sensors can be roughly divided into sensing technologies based on mechanical, optical, electrical, and acoustic principles.

Pulse pressure

Pulse waves are pulsations within arteries caused by cardiac contractions[36], containing rich cardiovascular health information, such as the elasticity of the artery blood vessel and the extent of arteriosclerosis[37]. Pulse diagnosis serves as an important diagnostic instrument in various traditional medical practices. However, traditional pulse diagnosis relies heavily on the personal experience and subjective judgment of experienced practitioners, leading to a pronounced subjectivity and a lack of uniform evaluation standards in the diagnostic results. Pressure sensors can objectively and effectively monitor many parameters of pulse waves, such as frequency, amplitude, pulse width, rise time, and transit time. By analyzing these parameters,

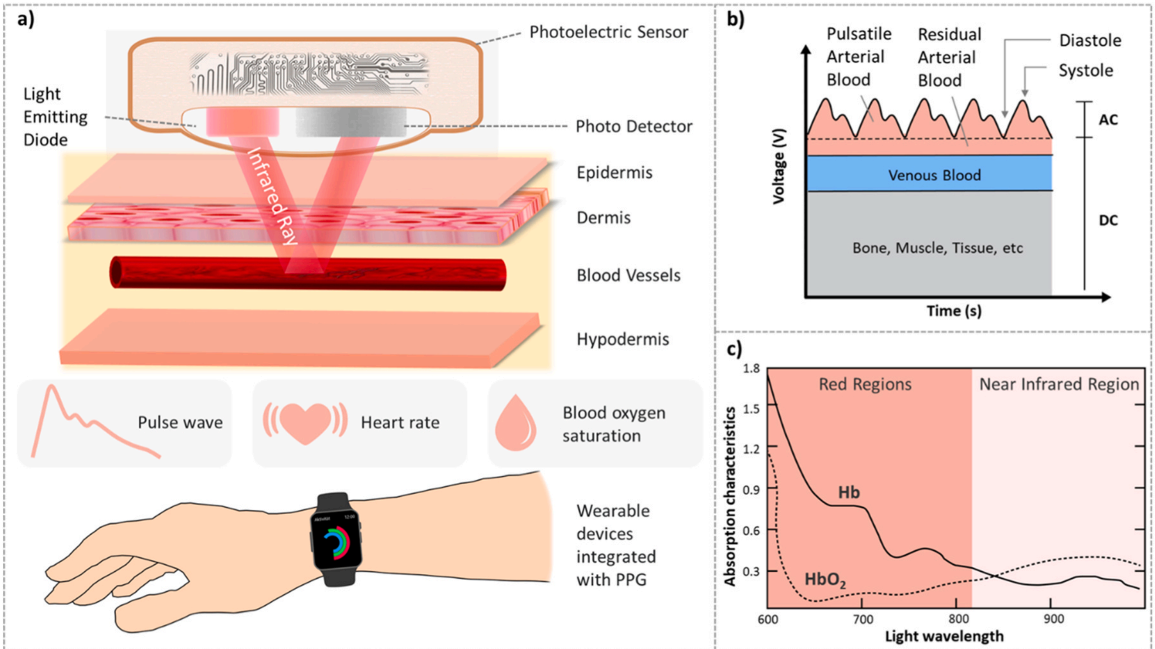

Fig. 4. Principles, detection methods and signal characterization of PPG. a) Schematic diagram of PPG sensor detection, b) Signal composition diagram of PPG sensor, c) Schematic diagram of PPG sensor measuring blood oxygen.

corresponding physiological indicators can be determined to ascertain cardiovascular health status.

Wearable pressure sensors, distinguished by their flexibility, stretchability, high sensitivity, quick response times, and excellent biocompatibility, have unique advantages in pulse wave monitoring, making them a hot research topic recently. The structure of the wearable pressure sensors mainly includes the sensing layer, electrode layers, and structural layers, as shown in Fig. 3a. Different sensing layers have different shapes of pulse wave signals due to different sensing principles. In pulse wave analysis, in order to simplify understanding, the pulse wave signal is described and analyzed in two forms: "differential waveform" and "integral waveform", as shown in Fig. 3b. The differential forms of waveforms are often associated with rapid dynamic pressure changes, such as the signals captured by piezoelectric sensors. Such sensors are very sensitive to instantaneous pressure changes and, therefore, are able to capture rapid pressure fluctuations caused by a beating heart. This waveform usually shows a higher peak value and a clear peak, which can be regarded as the "differential" form of the heartbeat pressure wave. The integral form of the waveform reflects the cumulative effect of pressure changes. For example, the signal captured by a piezoresistive or capacitive sensor is representative of the integral form of the pulse wave. Such sensors are more sensitive to sustained pressure changes, so their waveforms may be smoother, showing cumulative changes in pressure over time. This waveform can be viewed as the "integral" form of the heartbeat pressure wave. In short, the pulse waveform is a complex continuous waveform signal, which contains both the detailed information of small changes (differential waveform) and the characteristic information of the overall waveform (integral waveform)[38–40]. The differential form of pulse wave focuses on specific details and is particularly suitable for assessing the immediate response and health status of the heart, such as changes in heart rate, regularity of heartbeats, and strength of heart contractions. This waveform provides crucial information when monitoring transient yet significant cardiac events such as arrhythmias and premature heartbeats. Integral pulse waveforms are suitable for monitoring changes in BP, vascular compliance, and overall circulatory health, as shown in Fig. 3c. For monitoring chronic CVDs, such as hypertension and arteriosclerosis, the integral pulse waveforms can provide information on long-term blood flow dynamic changes[41]. By utilizing professional signal processing software or algorithms, these two types of waveforms can be converted into one another, catering to various clinical and research requirements.

Comprehending the specific characteristics and implications of the pulse wave is essential for the accurate assessment of cardiac and vascular health. Researchers have studied different feature points on a single pulse wave and determined that each feature point holds a unique meaning[42]. In the integral form of the pulse wave, as shown in Fig. 3b, the number 1 represents the main wave, the highest peak of the pulse wave. Studies have shown that changes in BP can also be reflected to some extent in the pulse waveform[43]. A single pulse waveform can be used to predict BP after a correlation between the two has been established. The height of the main waveform may reflect to some extent the pressure of the heart during contraction; the shorter the duration of the main waveform, the faster the heart is contracting. Number 2 represents the tidal wave, the first trough and peak after the main wave, reflecting the regurgitation phenomenon when the aortic valve closes. The number 3 represents the dicrotic notch, which is the local minimum value of the descent after the tidal wave. The position and depth of the descending gorge can reflect the elasticity and resistance state of the blood vessels, usually indicating diastolic BP. The number 4 represents the dicrotic wave, which is usually smaller than the tidal wave in the ascending section after the dicrotic notch and represents the blood refluxing to the left ventricle.

The differential form of the pulse wave usually contains seven characteristic points: As shown in Fig. 3b, point a represents the early stage of ventricular contraction, corresponding to the highest value of systolic BP; point b marks the end of the main wave, representing the beginning of ventricular relaxation; Point c reflects the intra-aortic regurgitation when the mitral valve is temporarily closed; point d is the descending isthmus area between the main wave and the tidal wave, and its length is related to the degree of BP reduction; point e represents the descending part of the slow wave, which is related to arterial elasticity and resistance; point f marks the time for the pulse wave to propagate to the terminal, reflecting the resistance state of the arteriole; point g reflects the microcirculatory response and terminal pressure [38]. These feature points are of great significance in assessing

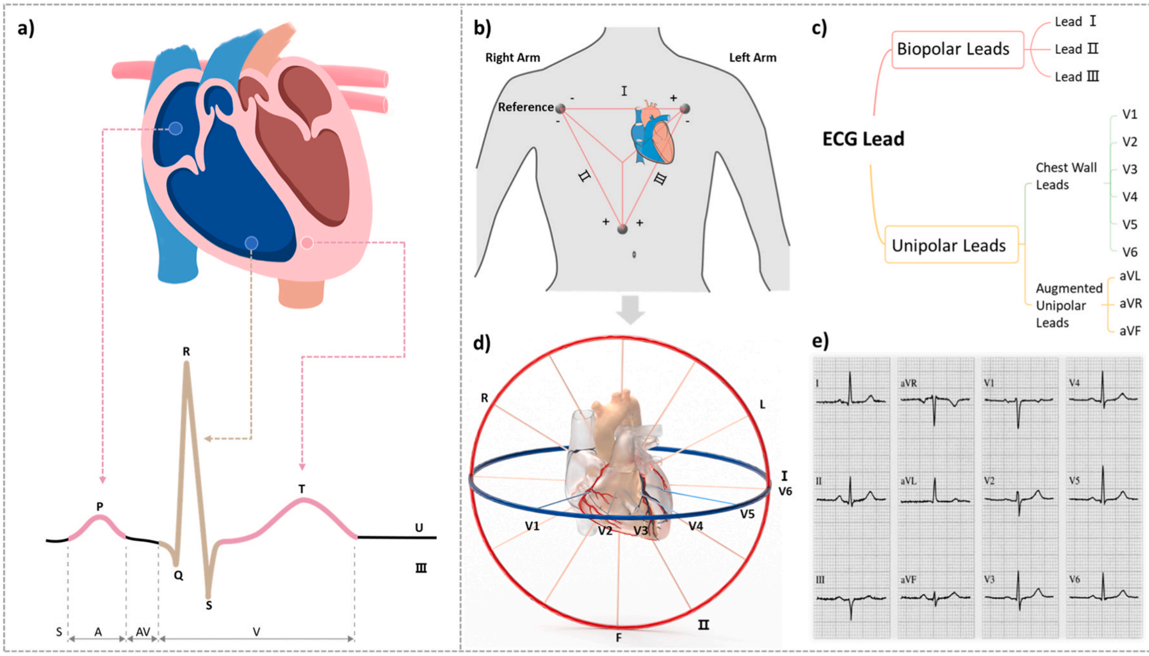

Fig. 5. Principles, detection methods and signal characterization of ECG. a) Schematic diagram of ECG sensor detection, b) Schematic of the measurement method for ECG, c) Classification of ECG leads, d) Schematic diagram of 12 lead monitoring direction model for ECG, e) Schematic waveform of monitoring direction model for 12 lead ECG.

cardiovascular health status. By further extracting, analyzing and calculating the amplitude and location information of these feature points, a series of important indicators reflecting cardiovascular health, such as arterial stiffness index, pulse wave velocity, augmentation index, pulse propagation time, etc., can be obtained. These parameters help physicians diagnose early signs of atherosclerosis, hypertension and other CVDs more accurately.

Pulse pressure sensors are typically used for mechanical signaling of superficial arteries and are highly sensitive to changes in vessel elasticity and thickness. However, they are susceptible to pulse position, depth variations, and motion artifacts, and have difficulty detecting deeper tissues. To address these limitations, the material selection and structural design of the sensor can be optimized to improve its accuracy and application range. In terms of material selection, the structural layer of wearable pulse pressure sensors usually uses polydimethylsiloxane (PDMS), silicone, polyurethane, and other elastic materials with good mechanical properties and biocompatibility. The conductive layer typically employs intrinsically stretchable materials such as liquid metal, conductive polymers, or utilizes stretchable patterned metal electrodes that can conduct the collected electrical signals. The sensing layer commonly utilizes sensitive materials such as piezoelectric materials, conductive polymers, and nanomaterials that can respond accurately and reliably to pressure changes. Regarding structural design, wearable pulse pressure sensors often adopt a multi-layer film structure, ensuring a close fit and conformal well to the skin. The application of microstructures, such as the design of micro-pyramid array patterns, further enhances the sensitivity of pressure sensors to minute pressure variations, thereby increasing the accuracy of cardiovascular health monitoring. In addition, the encapsulation structure design helps improve the durability and stability of the sensor, allowing it to maintain performance over long periods of use.

PPG

PPG is a non-invasive monitoring technique based on the principles of photoelectricity, used to detect blood volume changes in the vasculature of living tissues. In clinical medical practice, PPG is commonly utilized to record changes in blood perfusion, which can be assessed through the analysis of microcirculatory blood flow in the skin or other superficial body areas. The basic principle of PPG technology is to emit light (usually red, green, or near-infrared) from the surface of the skin and measure the amount of light reflected or transmitted back to the sensor through the tissue[44,45]. Due to the absorption characteristics of hemoglobin in the blood for specific wavelengths of light, the periodic changes in blood volume caused by the beating of the heart lead to changes in the amount of absorbed light, resulting in corresponding changes in photoelectric signals.

As shown in Fig. 4a, PPG mainly includes a light source (usually a light-emitting diode, LED) for emitting light, a photodetector for receiving penetrating or reflecting light and converting light signals, and the necessary signal processing circuits for analog-to-digital conversion and filtering circuits. In terms of signal detection, PPG stands out for its high sensitivity in detecting changes in blood volume, its non-invasive and convenient acquisition method, and its fast signal processing. Furthermore, the easy integration and scalability of PPG sensors render them a preferred option for contemporary wearable technology. Boasting benefits such as stable performance, capability for continuous monitoring, and cost-effectiveness, PPG sensors are now widely incorporated in most commercial wearable devices for daily health tracking and long-term monitoring.

In practical applications, when light from LED passes through skin tissue and is reflected back to the photosensitive sensor, there will be a certain attenuation. The flow of blood in arteries changes the absorption of light, while the absorption of light by muscles, bones, veins, and other connecting tissues remains basically unchanged. Therefore, when light is converted into electrical signals, the obtained signals can be divided into direct current (DC) signals and alternating current (AC) signals. Extracting the AC signal from it can reflect the characteristics of blood flow, enabling the acquisition of cardiovascular-related information such as pulse waves and heart rate, as shown in Fig. 4b.

Another important and widely used application of PPG sensors is the measurement of arterial oxygen saturation (SpO_2)[45]. Due to the presence of both oxygenated hemoglobin (HbO_2) and deoxyhemoglobin (Hb) in the blood, which have different light absorption rates, the differential optical absorption properties of HbO_2 and Hb can be utilized to measure SpO_2. Specifically, the absorption characteristics of HbO_2 and Hb in the wavelength range of 600–1000 nm are shown in Fig. 4c. It can be observed that the absorption coefficient of Hb is higher in the range of 600–800 nm, while the coefficient of HbO_2 is higher in the range of 800–1000 nm. Therefore, red light (600–800 nm) and near-infrared light (800–1000 nm) can be used to detect the PPG signals of HbO_2 and Hb, respectively, and the corresponding ratios can be calculated through programming to obtain SpO_2 levels. The normal range of SpO_2 is between 95 % and 100 %, when a SpO_2 level below 95 % indicates potential hypoxia in the body, suggesting possible cardiopulmonary dysfunction[46].

One of the key challenges in PPG technology is its sensitivity to motion artifacts and ambient light variations[47]. Motion artifacts can introduce signal noise, while skin characteristics (such as skin tone) can also affect the measurement results. Developing sensor housing materials that can resist motion artifacts is a potential solution[48]. Additionally, using high-performance photodetection materials and multi-wavelength LEDs can effectively improve light absorption and signal sensitivity [49–51]. Simultaneously, advanced signal processing algorithms can be utilized to filter out noise. These improvements help to reduce signal interference and improve the reliability of PPG sensors.

ECG

ECG is a crucial non-invasive method for diagnosing CVDs by recording the heart's electrophysiological activity during each cardiac cycle. It measures the sequential bioelectrical signals generated by the sinoatrial node, atrium, and ventricle, providing valuable data to assess heart health and diagnose various CVDs [52,53]. The results of ECG are usually displayed in the waveforms, taking the most common waveform of lead II as an example, as shown in Fig. 5a, which includes P-wave, QRS complex, and T-wave[54]. The P-wave represents atrial depolarization, which is the electrical activity of the atrial muscles. It reflects the beginning of atrial contractions, usually the first waveform on an ECG. The QRS complex represents ventricular depolarization, the most significant part of cardiac electrical activity. It reflects the contraction of ventricular muscles responsible for pumping blood from the heart to the whole body. Under normal circumstances, the duration of the QRS complex is relatively short, indicating that the ventricular depolarization process is rapid and synchronous. The T-wave represents ventricular repolarization, the recovery stage of ventricular muscle electrical activity. It appears after the QRS complex and is usually the last major waveform in the ECG. The shape, amplitude, and direction of the T-wave can provide important information about the uniformity of ventricular repolarization. The U-wave is usually smaller and appears after the T-wave. The exact origin of U-waves is still not fully understood, and it may be related to the late repolarization of ventricular muscles.

ECG is a comprehensive reflection of the electrical activity of countless myocardial cells in the heart, which means that ECG depicts the electrophysiological state of the entire heart rather than being limited to any single region. It forms a comprehensive electrophysiological map by capturing and integrating electrical signals from various parts of the heart. Measuring ECG signals requires connecting electrodes to multiple parts of the body. A simple ECG test only requires placing three electrodes on the torso to complete the measurement of leads I, II, and III, as shown in Fig. 5b. The standard ECG in medicine usually requires simultaneous twelve-lead testing, as shown in Fig. 5c, which includes bipolar leads(I, II, III) and unipolar leads. Unipolar leads can be divided into augmented unipolar leads (V1, V2, V3, V4, V5, V6) and chest wall leads (aVL, aVR, aVF). As shown in Fig. 5d, the twelve-lead ECG monitors the electrical activity of the heart from twelve different perspectives, resulting in a unique waveform pattern for each lead that produces electrical signals of different shapes and characteristics as shown in Fig. 5e. This multidimensional view provided by the multi-lead ECG is exceptionally beneficial for accurately locating cardiac abnormalities, such as pinpointing the specific areas of myocardial infarction [29], increasing the detection rate of pathological changes, and offering detailed analysis of arrhythmias. However, considering the professional operation requirement and the high costs involved, multi-lead ECG are generally served for clinical examinations. For some simple heart rate abnormalities, a single-lead ECG may suffice. Furthermore, single-lead ECG is more portable and user-friendly, making it suitable for integration with wearable devices for quick screenings and continuous monitoring of cardiovascular status, such as in-home health management scenarios.

ECG is used to diagnose various CVDs by detecting irregular

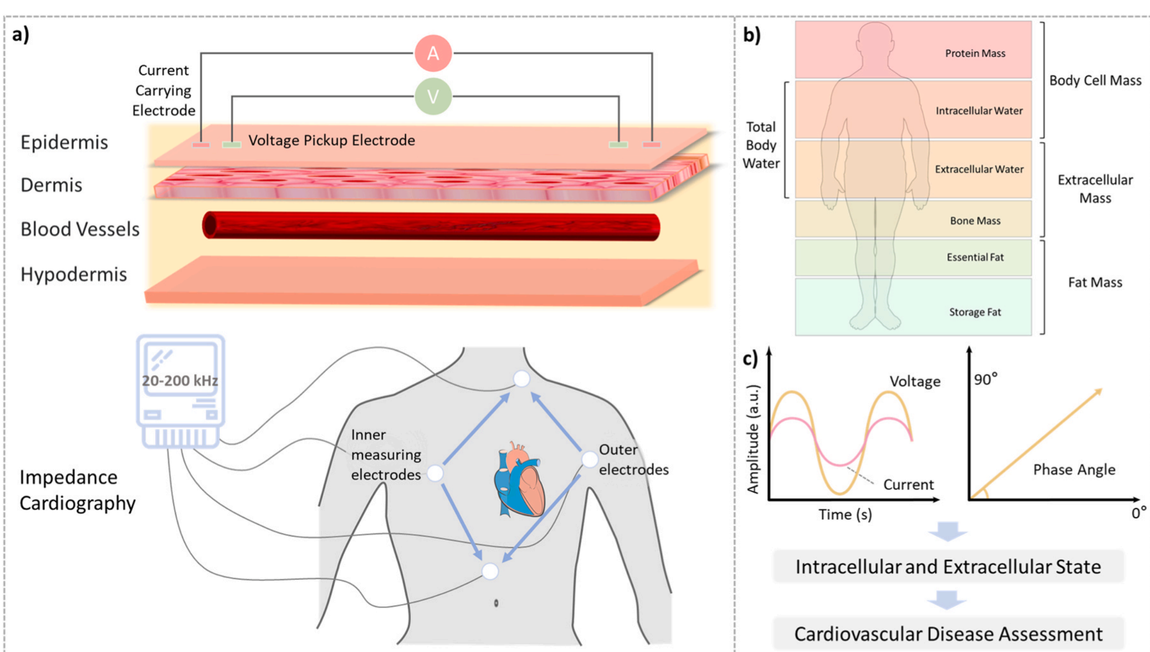

Fig. 6. Principles, detection methods and signal characterization of BIA. a) Schematic diagram of BIA measurement, b) Composition of electrical resistivity of different tissues in the human body, c) Flow chart of BIA used for CVDs analysis.

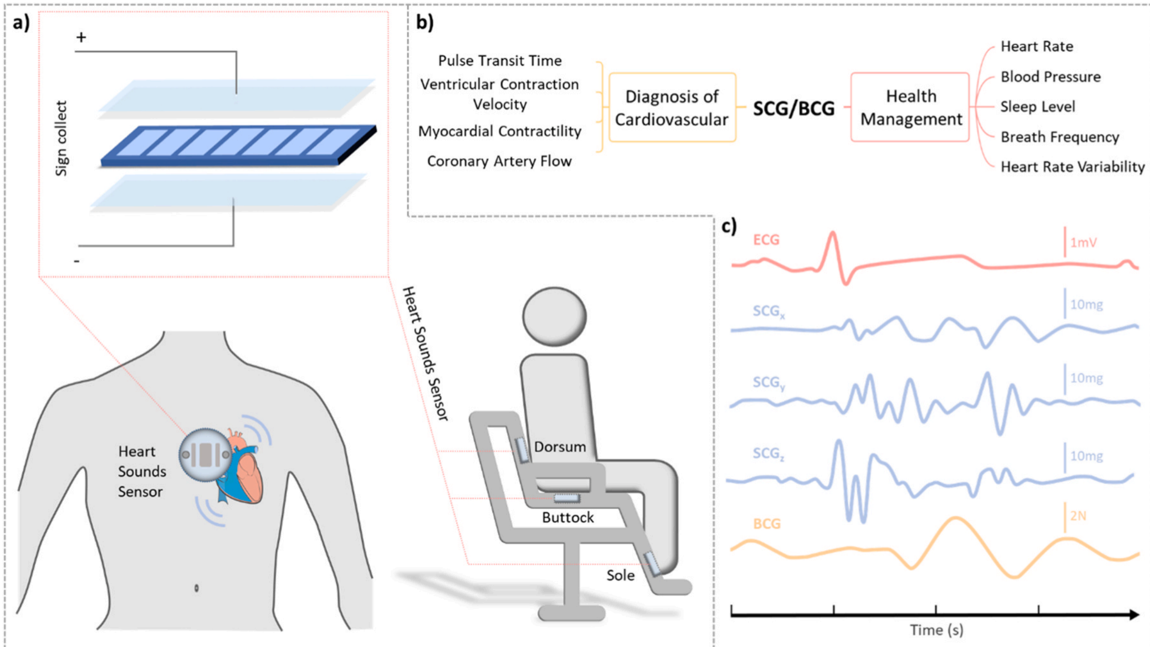

Fig. 7. Principles, detection methods and signal characterization of SCG/BCG. a) Schematic diagram of SCG/BCG measurement, b) SCG/BCG for CVDs and health management, c) Comparison of SCG/BCG and ECG waveforms.

heartbeat rhythms and changes in ECG features[55]. For example, ST-segment depression or elevation, and T-wave inversion can indicate myocardial ischemia, while ST-segment elevation and Q-wave deepening are associated with myocardial infarction[56,57]. QRS complex widening and ST-segment depression can suggest ventricular hypertrophy, and prolonged P-R intervals can indicate cardiac conduction block [58,59]. Additionally, ECG can be employed for dynamic monitoring of heart health, particularly using portable devices like Holter monitors, which continuously record ECG data over extended periods to track arrhythmias and other abnormal heart activities[60,61].

The main challenges in the application of ECG technology include the problems of signal interference and accuracy of electrode position [47,62]. Signal interference mainly originates from electromagnetic noise, electromyographic signals, and motion artifacts, which may significantly affect signal quality and diagnostic accuracy. To address these challenges, in recent years, hydrogel materials with high conductivity, good biocompatibility, and modulus matching that of the skin have been developed for use as ECG electrodes. These materials can improve signal quality, comfort, and stability, effectively reducing the impact of motion artifacts on the signal[63,64]. In addition, intelligent signal processing techniques (e.g., AI-based denoising algorithms) are being applied to analyze and correct interference in ECG signals in real time, further improving signal clarity and diagnostic accuracy[65–67]. These technological and material advances have significantly improved the reliability and utility of ECG monitoring.

BIA

Bioimpedance refers to the capacity of biological tissues to obstruct or resist the flow of electrical current[68]. BIA is a technique used to measure the biological impedance of the human body and calculate its composition. BIA applies an electrical stimulus (current or voltage) to the human body from the outside and measures the resistance and reactance when passing through human tissue, thereby inferring the conductivity and capacitance of the tissue. And the composition of the human body can be further calculated using formulas. Bioimpedance has the characteristics of fast detection speed, low cost, and non--invasiveness[69].

In cardiovascular health assessment, BIA techniques are used to monitor the activity and function of human organs. An impedance cardiogram is the information obtained when monitoring the human heart using bioelectrical impedance techniques. Using BIA technology, an excitation signal can be sent to the area being tested by placing a system of electrodes on the body's surface. The detection electrodes collect feedback information, and the corresponding impedance values and their changes are calculated by analyzing this data. Further, by comprehensively analyzing the impedance information, the physiological or pathological state of the corresponding part can be assessed, and thus whether a lesion exists therein. During a heart beat, blood is injected regularly into the aorta, resulting in changes in aortic volume, which in turn causes changes in impedance cardiogram. These changes simultaneously affect multiple physiological parameters such as cardiac output. Therefore, as shown in Fig. 6a, by measuring the bioelectrical impedance of the thoracic cavity and its changes, key physiological parameters such as cardiac output can be reflected[70]. In addition to the impedance cardiogram, BIA can also measure the body's structural composition, which mainly includes the measurement of cell mass, extracellular mass, fat mass and total body water, as shown in Fig. 6b [71]. The measurement of fat mass can assess the distribution of essential and stored fat, which is related to the risk of CVDs[72].

The quality of the bioelectrical impedance signal is mainly determined by the frequency and phase angle, as shown in Fig. 6c. The selection of different frequencies allows penetration of different layers of biological tissue, thus obtaining detailed information about the intra and extracellular environment, which is essential for health assessment of the cardiovascular system. Phase angle, as the phase difference between current and voltage, provides critical data about the electrical activity of heart cells and cell membrane function, helping to monitor the systolic and diastolic function of the heart, and thus assessing cardiac health. These measurements are valuable in the early diagnosis and management of CVDs[73].

In summary, the impedance cardiogram method is used to detect changes in blood flow in the cardiovascular system by placing electrodes on the body surface to monitor important physiological parameters, such as cardiac output, by utilizing the difference in electrical conductivity between blood and other tissues. Correct electrode placement and appropriate excitation frequency are key to accurate cardiovascular

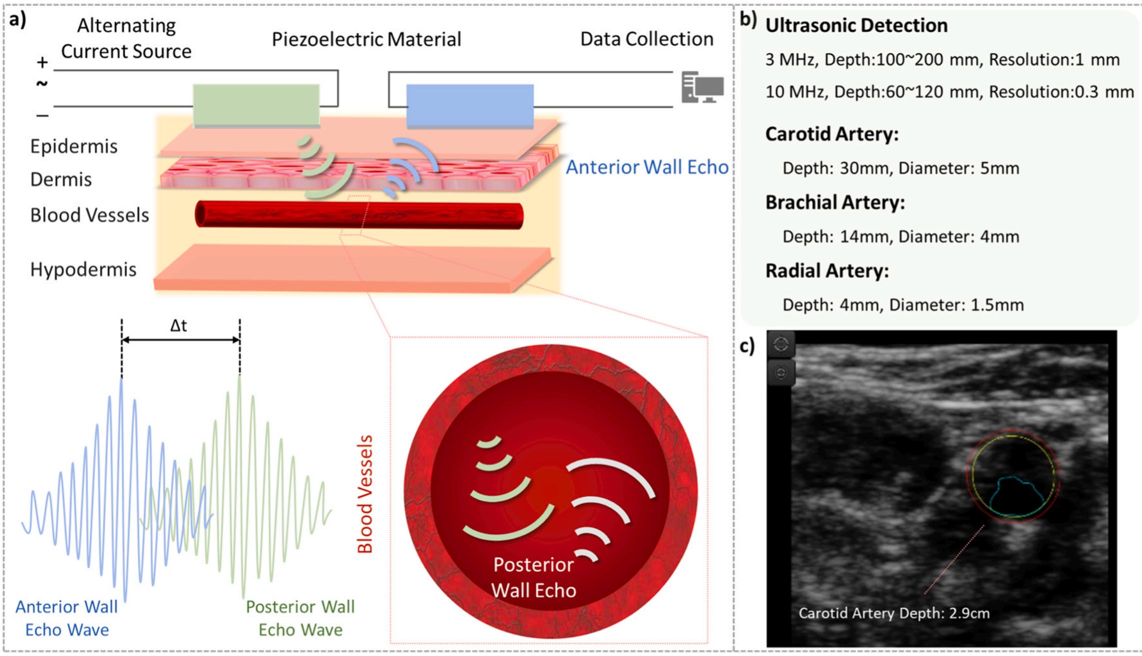

Fig. 8. Principles, detection methods and signal characterization of ultrasonography. a) Schematic diagram of ultrasound examination, b) Principle of ultrasound examination, c) Ultrasonography for detecting carotid artery. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[192].

monitoring using BIA[74]. In practice, the correct placement of the electrodes is crucial, as the complexity of the human structure and individual differences may lead to inaccurate test results. In addition, the choice of excitation frequency is also a critical factor, as different frequencies have different abilities to penetrate tissues, affecting the accuracy of measurement results. Therefore, rational selection of the excitation frequency as well as precise control of the electrode position are key to improving the value of electrical impedance measurements in cardiovascular health monitoring. Although this method provides critical blood flow information, the results are less specific and cannot be used directly to determine the cause of disease[75]. Therefore, the BIA method is primarily used as an adjunct to clinical diagnosis, in combination with other tests to enhance diagnostic accuracy.

SCG/ BCG

SCG is a non-invasive technique that monitors heart function and cardiovascular health by detecting cardiac vibrations on the chest surface, as shown in Fig. 7a[76]. This method utilizes an accelerometer to record mechanical vibration signals from the heart during its contraction and relaxation. SCG provides insights into the dynamics and structure of cardiac function, including blood flow characteristics and heart valve performance. It is instrumental in assessing the functional status and pathological alterations of the heart, as well as evaluating cardiac load. Additionally, SCG is valuable for tracking the outcomes of cardiac surgeries and the progress of cardiac rehabilitation. It holds promise for the ongoing assessment and management of patients with valvular heart disease, cardiomyopathy, and other cardiovascular conditions[77].

BCG is a technique that assesses cardiovascular function through the detection of mechanical vibrations and reactive forces generated by the heart's activity, impacting the entire body [78,79]. To capture these signals, sensors are usually placed on the back, buttocks, and soles of the feet (Fig. 7a)[80]. BCG offers valuable insights into the heart's contraction and relaxation phases, along with metrics on cardiac output and overall cardiovascular performance. It plays a crucial role in monitoring variations in cardiac load, including changes in blood volume and BP. Furthermore, BCG is instrumental in the evaluation of cardiovascular health, aiding in the diagnosis of coronary heart disease, and supporting various other cardiovascular investigations[81].

The distinctions between SCG and BCG lie primarily in their measurement principles, signal characteristics, and clinical applications, despite both utilizing mechanical sensors to capture heart-related signals for evaluating heart function and cardiovascular health. SCG focuses on the vibrations produced by the myocardium and the heart valves' opening and closing processes. This allows SCG to provide detailed information on heart muscle contraction and relaxation, heart valve function, pulse wave transmission time, ventricular contraction velocity, myocardial contraction force, and coronary artery blood flow, as shown in Fig. 7b. The frequency of the SCG signal is usually less than 25 Hz[82]. These signals are characterized by short rise and fall times and distinct and sharp pulse shapes, reflecting the activity of the myocardial wall, as shown in Fig. 7c. BCG, on the other hand, captures the body's overall reaction to cardiac pulsations, offering insights into cardiac output and overall cardiovascular function. It can provide physiological indicators such as heart rate, BP, sleep level, respiratory rate, and heart rate variability[83]. BCG signals are lower in frequency, usually ranging from 0.8 Hz to 15 Hz, and exhibit longer rise and fall times with smoother pulse shapes and appearance[84]. This difference in signal characteristics is due to BCG's focus on the overall bodily response to the heart's activity rather than the direct mechanical actions of the heart itself. In addition, the units of SCG and BCG are not the same. SCG records the acceleration of the chest wall and has mili-gravitational units (mg), while BCG represents the displacement of the subject's center of mass, which is then converted to units of force by the spring constant of the graduated platform and has units of newtons (N)[85].

In summary, SCG provides a more localized, high-frequency analysis of heart function, which is particularly useful for assessing myocardial and valvular activity. In contrast, BCG offers a broader perspective, capturing the overall cardiovascular system's response to heartbeats, which is useful for evaluating cardiac output and general cardiovascular health. Both techniques utilize accelerometers—SCG uses chest-mounted sensors, while BCG employs sensors on various body parts. Although both methods are suitable for the detection of cardiac load,

Table 1
Comparison of wearable cardiovascular monitoring technologies: signal sources, detection sites, signal types, advantages, and limitations.

Technology	Signal source	Detection site	Signal type	Advantages	Limitations
Pulse pressure	Arteries	Superficial arteries	Mechanical signal	Highly sensitive to changes in vascular elasticity and thickness, simple device structure and low cost	Limited sensitivity to deeper tissue variations, wide variation in pulse location and depth, susceptible to motion artifacts
Photoplethysmography	Photoemitter	Fingertip, wrist	Optical signal	Easy to use, advantageous for monitoring blood volume, portable and low cost	Accuracy can be influenced by skin characteristics, affected by light noise, susceptible to motion artifacts
Electrocardiogram	Sinoatrial node	Hands, feet, chest	Electrical signal	Accurate detection of electrical activity in the heart, essential for diagnosing arrhythmias and myocardial infarction	Prone to noise interference, requires precise electrode placement, susceptible to skin contact quality
Bioimpedance analysis	AC signal generator	Artery blood vessel, chest	Electrical signal	Detectable body fluid volume, suitable for heart failure management, easy to use	Affected by electrode positioning, hydration levels, large individual differences, accuracy limited by measurement principle
Seismocardiography/ ballistocardiography	Heart	Chest	Mechanical signal	Suitable for cardiac mechanical activity analysis, high temporal resolution, detectable cardiac load, easy to deploy	Highly sensitive to physical movement and environmental vibrations, susceptible to noise
Ultrasonography	Ultrasonic emitter	Most blood vessels, heart	Acoustic signal	Visualization structures of the heart and blood vessels, suitable for diagnosing blood flow-related diseases, real-time imaging	Dependent on professional operating experience, higher equipment cost, complex signal processing

they face challenges with noise due to their sensitivity to physical movement and environmental vibrations. The development of microelectromechanical systems (MEMS) technology has made SCG/BCG sensors more precise, compact, and easy to integrate. Furthermore, flexible electronics technology allows these sensors to be designed to better conform to the contours of the human body, effectively reducing motion noise and improving signal quality and comfort. In terms of materials, some new piezoelectric materials, with their excellent mechanical and electrical properties, can significantly enhance the sensitivity, resolution, stability, and dynamic range, enabling the sensors to perform exceptionally well in detecting extremely weak cardiovascular vibration signals.

Ultrasonography

Ultrasound refers to sound waves generated by an object (sound source) vibrating at frequencies above 20,000 Hz, exceeding the audible range of the human ear. Compared to light and heat, ultrasound boasts a significant penetration depth in human tissues. Ultrasonography is a technique that utilizes the physical properties of ultrasound waves and the acoustic parameters of human tissues to create images. Renowned for being non-invasive, highly precise, capable of deep penetration, and free from ionizing radiation[86,87], it is extensively used in clinical examinations and medical diagnostics, earning the moniker "the doctor's eyes." Since the 1950s, ultrasound technology has evolved from B-mode ultrasound[88], color doppler ultrasound[89], three-dimensional ultrasound[90], and four-dimensional ultrasound [91,92] to today's flexible wearable ultrasound patches, enabling dynamic imaging from two-dimensional to four-dimensional as well as real-time, continuous long-term monitoring [93–96].

The core component of an ultrasound system is the transducer, which is usually composed of piezoelectric material. When AC voltage is applied to piezoelectric materials, it will generate mechanical vibration or deformation. This vibration can be converted into ultrasonic signals through piezoelectric sensors and propagated to internal tissues of the human body. When ultrasound passes through human tissues, it will reflect and refract at the interface between different tissues such as blood vessels. These reflections and refractions can cause changes in the path of ultrasound, resulting in the formation of echo signals. The echo signal of ultrasound can be captured by the probe receiver and converted into a visualized image through signal processing and imaging algorithms to provide detailed information on the internal structure of the human body, as shown in Fig. 8a.

In the field of ultrasound imaging, depth of detection and resolution are key metrics for evaluating the performance of imaging technologies [97,98]. For example, as shown in Fig. 8b, ultrasound with a frequency of 3 MHz provides a detection depth of 100–200 mm with a resolution of 1 mm. Ultrasound at 10 MHz, on the other hand, provides a depth of detection of 60–120 mm, but with an increased resolution of 0.3 mm [99]. This difference suggests that higher-frequency ultrasound is more effective in resolving fine structures, although at a reduced depth of penetration. This difference in resolution is particularly important in vascular imaging applications such as imaging of the carotid, brachial and radial arteries. The carotid arteries are typically 30 mm deep and about 5 mm in diameter, making them suitable for fine imaging using high-frequency ultrasound, and the actual ultrasonography of the carotid arteries by the ultrasound device is shown in Fig. 8c. The smaller diameters of the brachial and radial arteries (diameters of 4 mm and 1.5 mm, respectively), located at a depth of 14 mm and 4 mm, respectively, also suggest that clearer images of the vessel wall and surrounding tissues can be obtained using higher-frequency ultrasound. Therefore, clinical diagnosis and disease monitoring in cardiovascular health monitoring requires the selection of an appropriate ultrasound frequency based on the depth of the location to be detected and the required resolution [100].

Ultrasonography can also be used to evaluate cardiovascular function. For example, in vascular ultrasound, anterior wall echoes reflect features of the anterior surface of the tissue, such as organ morphology and location, while posterior wall echoes reflect information about the posterior surface of the tissue, such as organ contour and reflectivity [87]. The time difference between the anterior and posterior wall echoes can be used to calculate the speed of sound and to assess the nature and state of the tissue [101]. By measuring the time difference, information about tissue density, elasticity and sound transmission properties can be obtained [102]. In addition, ultrasonography can be used to evaluate cardiac function [95], and to calculate central venous pressure in blood flow imaging [96]. Ultrasonography can also be used to observe the working conditions of heart valves [103]. Through ultrasonography, doctors can check whether the valve opening and closing are normal, and whether there is valve disease, such as stenosis or incomplete closure, to guide treatment and surgical decision-making.

Ultrasonography utilizes acoustic signals to effectively visualize the structures of the heart and blood vessels, providing real-time imaging that is invaluable for diagnosing blood flow-related diseases. Despite its benefits, it relies heavily on professional operating experience and incurs high equipment costs, coupled with complex signal processing requirements. Addressing these challenges could involve developing user-friendly systems with automated image processing capabilities and exploring cost-effective equipment solutions to make ultrasonography more accessible and easier to use in various application scenarios.

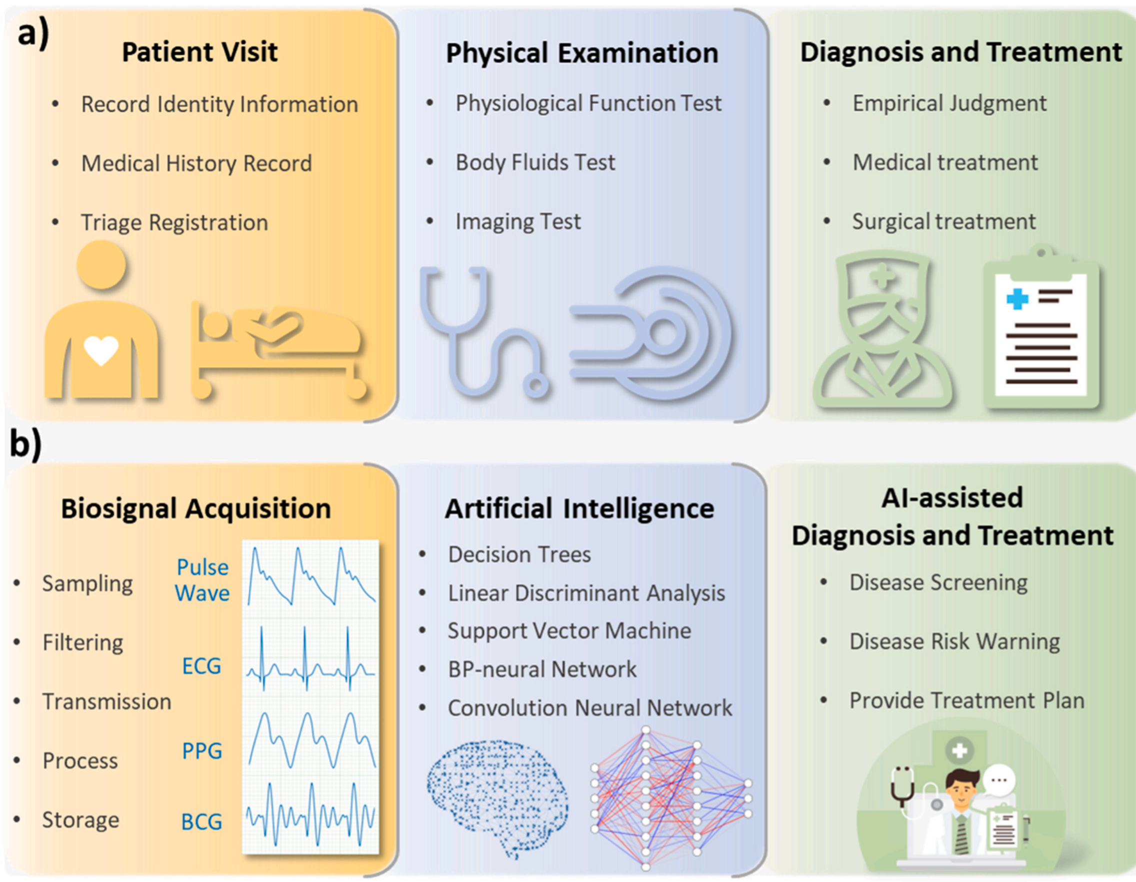

Fig. 9. Comparison between traditional methods of cardiovascular health monitoring and disease diagnosis and diagnosis combined with ai technology. a) The traditional cardiovascular health monitoring process mainly includes patient visit, physical examination, diagnosis and treatment. b) The cardiovascular health monitoring process combined with AI mainly includes physiological signal acquisition, AI model establishment, and AI model assisted diagnosis and treatment.

Comprehensive perspectives in cardiovascular health monitoring

Cardiovascular health monitoring relies on a range of technologies, which can be categorized into two main groups. The first category is the direct measurement of signals generated by cardiovascular activities, such as pulse pressure, ECG, SCG/BCG. These signals are directly captured by corresponding smart wearable devices, which are able to reflect the physiological state of the cardiovascular system in real-time. The second category is the method of collecting reflected signals through physical means such as light, electricity, sound, etc., which are used in the human body without harmful, including PPG, BIA and ultrasonography [104–108]. Unlike direct measurement of signals that are mainly reflected on the body surface, methods that utilize physical signals such as light, electricity, and sound can detect deeper cardiovascular states. For example, PPG reflects changes in blood volume, BIA analyzes tissue composition, and ultrasonography provides detailed images of cardiac structures [109–113]. While these technologies collectively enhance the ability to diagnose and manage CVDs, each has inherent limitations. Table 1 compares and summarises different non-invasive monitoring methods regarding the signal source, detection site, and signal type for each technology, alongside their advantages and limitations[114–118].

In practical clinical scenarios, it is essential to select the appropriate diagnostic method tailored to the patient's specific symptomatic characteristics to analyze the cardiovascular structure and functional status, leading to an accurate diagnosis. For certain complex conditions, it may also be necessary to employ multiple diagnostic techniques simultaneously, allowing for a comprehensive assessment from various angles. Multimodal sensing acquires a variety of cardiovascular information by collecting various physiological signals from different perspectives, such as mechanical, optical, electrical, and acoustic, and integrating multiple physiological data. In addition, multidimensional cardiovascular information can also be obtained from clinical case reports, imaging images, and biochemical indicators[119–121]. However, there are significant challenges in integrating these diverse data sources, exploring their interconnectivity, and establishing deep mapping relationships between multimodal signals and multidimensional cardiovascular health states. To address these problems, there is an urgent need for a technology that can efficiently process and interpret complex heterogeneous data [122,123]. AI can enhance data analysis and interpretation, reducing the complexity and individual variability encountered in traditional data analysis[124,125]. By incorporating AI, the precision and reliability of cardiovascular monitoring could be further improved, leading to more accurate and comprehensive evaluations of cardiovascular health.

AI in cardiovascular health monitoring

Traditional cardiovascular health monitoring and treatment usually rely on regular physical examinations and doctors' experienced diagnosis [126]. Nevertheless, considering the high costs and time investment associated with regular health screenings, many patients at risk experience delayed diagnoses. Additionally, the variability in doctors' experience may result in differing diagnostic conclusions. AI technology, particularly machine learning and deep learning, offers powerful tools for enhancing cardiovascular health monitoring, particularly in medical data process and diagnostic support [127–130].

In traditional cardiovascular health monitoring, as shown in Fig. 9a, doctors first need to inquire about the patient's identity information and record their medical history and symptoms, such as chest pain, breathing difficulties, and palpitations. Then, during the physical examination, the doctor looks at the patient's current physiologic function tests, body fluids, and imaging tests, such as measuring the patient's BP, pulse, ECG, and ultrasonography, to determine if there are any signs of abnormality, such as atrial fibrillation or a heart murmur. Finally, the doctor will take appropriate diagnostic and therapeutic approaches, such as medication and surgery, based on the test results and existing experience[131]. These methods rely heavily on manual recordings and routine screening devices, which are inefficient for continuous monitoring and may delay early detection and treatment [132].

AI technology offers transformative solutions to these limitations by enhancing both the data processing capabilities and diagnostic accuracy of cardiovascular monitoring systems. For example, during the biosignal acquisition phase, AI can improve signal quality by applying advanced preprocessing techniques, such as denoising and artifact removal, to raw data obtained from wearable sensors. This is particularly valuable in technologies like pulse pressure monitoring and PPG, where signal artifacts due to motion or external light can compromise data validity. Moreover, AI algorithms can enhance ECG signal analysis by filtering out noise and accurately identifying cardiac events, even when signals are weak or noisy. In the case of BIA, AI-driven models can adjust for individual variations in body composition and hydration levels, leading to more consistent measurements. SCG/BCG and ultrasonography also benefit from AI's ability to differentiate true cardiac signals from background noise, ensuring that mechanical and acoustic assessments are more reliable.

AI technology provides transformative solutions to the limitations of cardiovascular monitoring systems by enhancing data processing and diagnostic accuracy. In PPG and pulse pressure monitoring, AI can significantly improve signal quality by employing advanced preprocessing techniques such as denoising, artifact removal, and adaptive filtering. These methods effectively address common issues like motion artifacts and external light interference, which often compromise data validity[133]. For ECG analysis, AI-driven algorithms utilize machine learning models to accurately identify cardiac events, such as arrhythmias, even when signals are weak or obscured by noise. This is achieved through sophisticated noise filtering and pattern recognition techniques, which enhance the reliability of ECG diagnostics, especially in dynamic or ambulatory monitoring environments[62]. In BIA, AI algorithms account for variations in body composition, hydration, and other physiological factors that can affect measurements. By dynamically adjusting the analysis models, AI ensures more consistent readings, which is critical for accurate assessments of body impedance. Similarly, in SCG and BCG, AI techniques differentiate true cardiac signals from background noise, such as body movements or environmental vibrations. Advanced feature extraction and classification algorithms improve the precision of these mechanical and acoustic assessments, making them more reliable even in less controlled settings. AI also plays a crucial role in ultrasonography by addressing the challenges associated with the high volume and complexity of image data. AI-powered image processing algorithms enhance the resolution, segmentation, and overall clarity of ultrasound images, facilitating more precise visualization of cardiac structures and blood vessels. Furthermore, AI can automate the identification of key anatomical features, reducing dependence on operator experience and minimizing variability in image interpretation. This results in more consistent and accurate real-time imaging, which is essential for diagnosing blood flow-related conditions. Overall, AI significantly improves the performance and reliability of various cardiovascular monitoring technologies by enhancing data quality, reducing noise, and automating complex diagnostic tasks.

AI-driven intelligent monitoring systems utilize wearable sensors for efficient data acquisition, including sampling, filtering, transmitting, processing, and storage, as shown in Fig. 9b [134]. AI techniques like decision trees, support vector machines, and neural networks automatically identify disease patterns and provide accurate diagnoses and personalized treatment plans [135,136]. The ability to process and analyze massive amounts of data is key for identifying disease patterns and predicting risks [137]. Moreover, AI algorithms can accelerate the diagnostic process and improve decision-making accuracy, especially in the detection of subtle patterns that may indicate early signs of CVDs.

In the field of cardiovascular health monitoring, the application of intelligent wearable devices is becoming increasingly widespread, and its core relies on the integration and optimization of machine learning and deep learning algorithms. Machine learning algorithms, such as decision trees, support vector machines, and random forests, are widely used due to their effectiveness in processing small and feature specific datasets [135]. These algorithms are suitable for performing classification tasks such as cardiovascular conditions, where decision trees analyze data by simulating decision paths, support vector machines construct hyperplanes in high-dimensional space to maximize inter class margins, and random forests improve prediction accuracy and reduce the risk of overfitting by constructing multiple decision trees. On the other hand, deep learning algorithms, especially convolutional neural networks, recurrent neural networks, and their variants of long short-term memory networks, are highly praised for their excellent performance in processing large-scale datasets and recognizing complex patterns[36]. These deep learning models are particularly suitable for analyzing complex biological signal data such as ECG[62]or PPG[133], which can identify abnormal patterns such as arrhythmia. Machine learning models perform well in small datasets that require clear decision logic, while deep learning models demonstrate their advantages in situations with large amounts of data, complex patterns, and the need for highly automated analysis[18]. Therefore, by integrating machine learning and deep learning, intelligent wearable devices continuously monitor cardiovascular health, adapting to individual variability in real-time, enhancing detection and providing actionable insights for personalized health management[138,139].

Nowadays, a variety of wearable cardiovascular monitoring devices have emerged, offering diverse functionalities for the prevention and prognosis of CVDs[138]. Compared to traditional methods, AI-equipped devices can process large datasets rapidly, providing timely health guidance [140]. Additionally, these devices excel in long-term tracking, offering new strategies for managing conditions like arrhythmias, atrial fibrillation, and hypertension. Through continuous data analysis, they can identify potential health risks, remind users to take preventive actions, and recommend personalized lifestyle adjustments. This technology also enhances doctor-patient interaction, allowing remote access to real-time health data for more precise and timely care. In summary, the integration of wearable devices with AI technology marks a new era in cardiovascular health management, characterized by enhanced intelligence, personalization, and connectivity.

Application of emerging wearable devices and ai enhancement for cardiovascular health monitoring

With the advancement of new materials, bionanotechnology, micro and nanofabrication processes, and the microelectronics industry, a range of high-performance, multi-functional wearable cardiovascular health monitoring devices have been developed. Utilizing advanced sensing mechanisms, these devices are capable of monitoring key indicators such as heart rate and BP in real-time and providing a more comprehensive assessment of cardiovascular health through continuous data collection. Integration of AI technology further enhances these devices by enabling them to not only collect data, but also intelligently analyze this information to provide support in predicting cardiovascular events, personal health management, and paramedical decision-making. For example, through continuous monitoring and AI algorithms, these devices are able to recognize early signs of arrhythmia and notify users and healthcare providers in a timely manner, potentially preventing serious cardiovascular events from occurring. In addition, AI-enhanced cardiovascular health monitoring devices can provide personalized health advice based on an individual's lifestyle and historical health

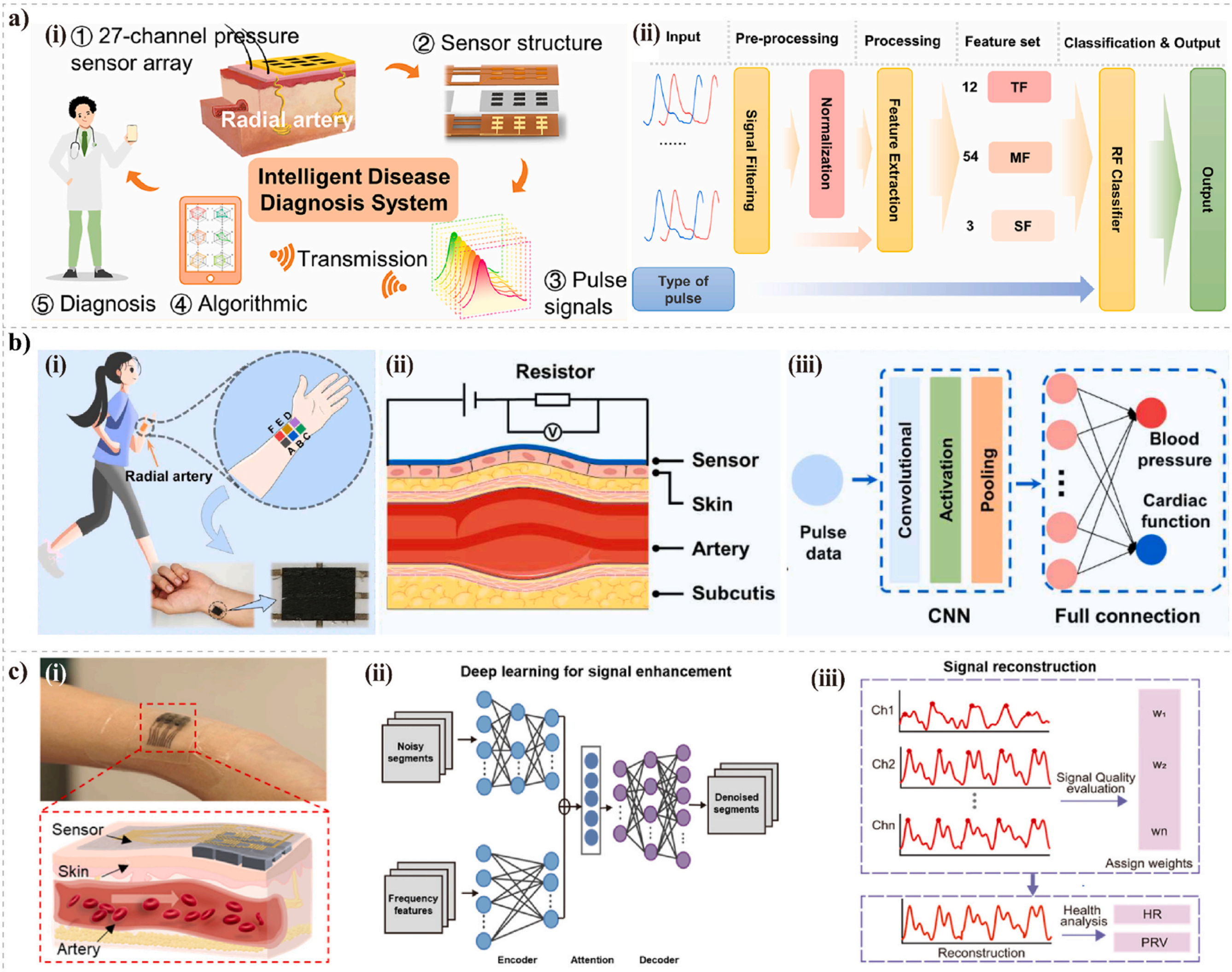

Fig. 10. Wearable active pulse pressure sensors. a) Multi-channel flexible pulse sensing array for intelligent disease diagnosis system. (i) Schematic diagram of the intelligent disease diagnosis system based on flexible pressure sensors. (ii) Schematic diagram of machine learning for automatic pulse recognition. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[146]. b) Piezoresistive pressure sensor for continuous monitoring of BP and heart function. (i) Schematic diagram of the pulse monitoring system. (ii) Schematic diagram of the deformation of the pressure sensor caused by the radial artery pulse and its working mechanism. (iii) Architecture of the deep learning model. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[106]. c) A deep learning-assisted skin-integrated pulse sensing system for reliable pulse monitoring and cardiac function assessment. (i) Schematic diagram of a multi-channel pulse array attached near the artery. (ii) Schematic diagram of an autoencoder model for signal enhancement. (iii) Schematic diagram of an inverse variance weighting algorithm for pulse signal reconstruction. Reproduced with permission[144], Copyright 2024, Elsevier Ltd.

data. The development of these technologies shows great promise and potential for application both in the medical field and personal health maintenance.

Wearable devices based on pulse pressure sensors

In recent years, innovative approaches to flexible biomedical sensors have shown a surge of interest. Wearable pulse pressure sensors represent a rapidly evolving technology, distinguished by their ability to sensitively detect subtle mechanical signals, thereby establishing a dependable tool for the detection of human pulse pressure. Devices designed for the continuous, non-invasive monitoring of vital signs employ these pressure-sensitive sensors and benefit from their high sensitivity, stability, and conformability in detecting pulse pressure [141–143]. Here, we select typical cases of several burgeoning forms of pulse pressure sensors to introduce their relevant applications in cardiovascular status assessment. According to whether an external power supply is required, these sensors can be divided into active and passive types, among which active sensors include piezoresistive[144–146] and capacitive[147,148] types, while passive sensors include piezoelectric [149], triboelectric[150,151], and magnetoelastic[152] types.

Liu et al. designed a BP and cardiac monitoring system using a flexible multi-channel pulse pressure sensor array with carbonized silk fabric and deep learning algorithms, achieving high sensitivity and real-time pulse monitoring, suitable for early CVDs diagnosis (Fig. 10a) [146]. Building on similar principles, Pang et al. developed a flexible piezoresistive sensor with a PDMS and metal-coated polyurethane nanofiber structure, enhancing its ability to detect pressure, shear, and torsion, crucial for precise cardiovascular assessments[145]. Expanding on these advancements, Li et al. introduced a health monitoring system with a piezoresistive strain sensor array and deep learning algorithms that achieved an impressive BP prediction accuracy ($<$1 mmHg) by analyzing wrist pulse signals (Fig. 10b)[106]. Jia et al. further integrated flexible pulse pressure sensors with deep learning-assisted signal enhancement in a skin-integrated system, offering reliable pulse signal monitoring for dynamic and static conditions, facilitating heart rate and

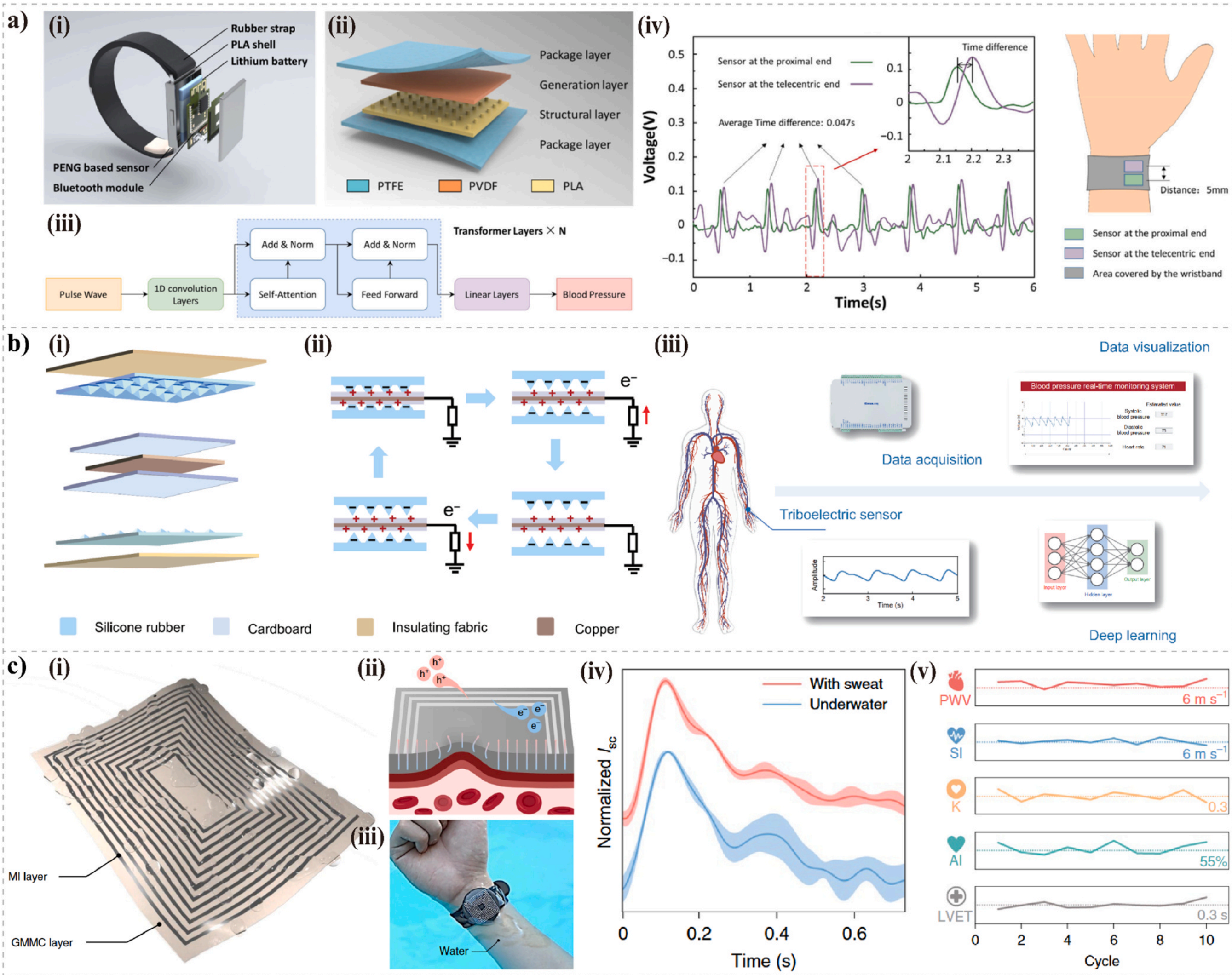

Fig. 11. Wearable passive pulse pressure sensors. a) Piezoelectric pressure sensor for BP prediction. (i) The structure of BPPW and the materials used in each part. (ii) The structure and materials used of sensor in BPPW. (iii) The process of BPPW's deep learning model establishment. (iv) The difference in time between two sensors at different locations. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[149]. b) Triboelectric pressure sensor for BP prediction. (i) Schematic illustration of the double sandwich structure. (ii) Working principle of the triboelectric sensor. (iii) The flow of system frame diagram. Reproduced with permission, Copyright 2022, Springer Nature[150]. c) Magnetoelastic pressure sensor for health monitoring in humid environments. (i) The structure of a magnetoelastic generator. (ii) Schematic of the arterial pulse sensing mechanism of the magnetoelastic generator. (iii) Photograph showing a magnetoelastic generator worn on the wrist underwater. (iv) Comparison of the arterial pulse waveforms obtained from the magnetoelastic generator underwater and with sweat. (v) Key arterial parameters extracted from the fine structure of the pulse waveform obtained with artificial perspiration. Reproduced with permission [152], Copyright 2022, Springer Nature.

variability analysis (Fig. 10c)[144]. Additionally, Pang et al. advanced sensor design with a capacitive pulse pressure sensor featuring a biomimetic structure, significantly improving sensitivity and reducing hysteresis, aimed at evaluating heart failure risk via jugular venous pulses[147].

Piezoelectric sensors are usually one of the common types of sensors used to detect pulse wave signals. They have good sensitivity and time resolution, and can detect and record subtle changes in pulse waveform. Tan et al. designed an AI-enhanced BP prediction wristband (BPPW) based on piezoelectric nanogenerators[149]. BPPW adopts a columnar array microstructure to improve the output performance of piezoelectric sensors, and combines supervised Transformer deep learning models to predict BP by combining collected pulse wave data with pre-established regression models. BPPW can achieve a high signal-to-noise ratio of 29.7 dB and a BP prediction ability with an error of less than 4 mmHg. And it achieved three consecutive days of BP monitoring, proving that BPPW has the ability to monitor BP for a long time, which is of far-reaching significance for long-term cardiovascular health monitoring, as shown in Fig. 11a. Li et al. also introduced a thin, soft, miniaturized system (TSMS) for continuous arterial BP monitoring, which addresses the issues of bulkiness and poor user-device interface in existing technologies[153]. This system combines a piezoelectric sensor array with an active pressure adaptation unit and advanced machine learning, achieving Grade A measurement accuracy. The TSMS's compact design and effective pressure control allow for accurate, real-time BP monitoring in a wearable format, enhancing both usability and performance.

Triboelectric sensors are widely used in cardiovascular health monitoring due to their high cost performance, wide selection of materials, and simple working principles. Ran et al. proposed a triboelectric sensor based on a new sandwich structure [150]. A sensitivity of 0.89 V/kPa is achieved in the linear range of 0 ~ 35 kPa, so this triboelectric sensor can easily capture the pulse signal at the radial artery. In addition, a new method for estimating BP based on pulse waves

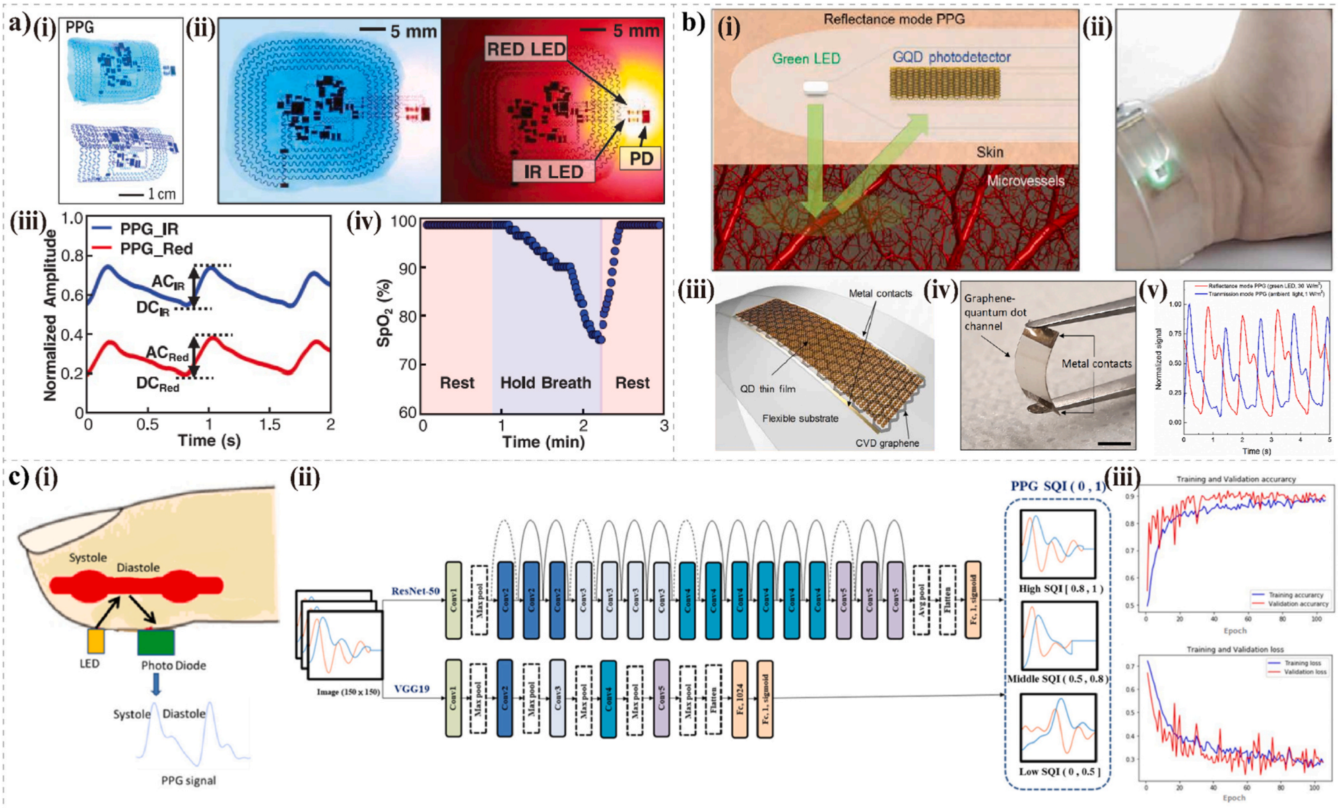

Fig. 12. Wearable PPG sensors. a) PPG sensors for newborn health monitoring. (i) Images and finite-element modeling results for PPG devices bent. (ii) Device for capturing PPG data during operation in a lighted and a dark room. (iii) Convention for calculating direct and alternating components of PPG waveforms collected in the red and IR. (iv) The change in SpO2 detected by the sensor after holding breath. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[154]. b) A novel flexible and transparent wearable device based on graphene and semiconductor quantum dot sensitization. (i) Schematic of PPG in reflectance mode. (ii) HR monitoring bracelet based on reflection mode PPG to extract vital signs from wrist. (iii) Schematic illustration of the assembly of graphene and QDs on a flexible substrate. (iv) Photograph of macroscale PD on the PET substrate. (v) Scale bar, 5 mm. Normalized PPG readings for transmission and reflectance modes of operation. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[49]. c) PPG sensors combined with DCNN to improve PPG quality. (i) Schematic of PPG in reflectance mode. (ii) DCNN algorithm network architecture. (iii) Accuracy and loss profile for training and validation in the model. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[155].

combined with user background information is proposed. This method only measures a set of pulse wave signals, and then based on the deep learning model of a multi-network structure, it can predict systolic BP and diastolic BP, promoting the development of wearable devices for continuous and portable BP prediction, as shown in Fig. 11b. Yao et al. also developed a novel wearable system for BP monitoring, which combines a bionic nanocolumn layer-based triboelectric pulse sensor with personalized machine learning (PLSR)[151]. The innovation lies in the sensor's design, inspired by cicada wing structures, which enhances the detection sensitivity of pulse waveforms. By integrating this sensor with PLSR, the system can accurately tailor BP predictions to individual physiological differences, offering an improvement over standard methods that often struggle with individual variability.

Since the discovery of the giant magnetoelastic effect in soft systems in 2021, magnetoelastic sensors have become a key technology for wearable devices due to their small size, excellent waterproofness, and biocompatibility. Zhou et al. invented a soft magnetic elastic sensor as a pulse pressure sensor, whose elastic modulus can be similar to human skin and tissue[152]. Since the magnetic field can penetrate water, the magnetoelastic sensor can be worn on the wrist to continuously and stably provide real-time health data even when sweating or spraying artificial sweat. It can be used for human cardiovascular health monitoring and disease diagnosis, as shown in Fig. 11c.

Wearable devices based on PPG sensors

The relentless progress of photoelectric technology has considerably broadened the utilization of PPG in the medical field. PPG waveforms offer multifaceted insights into cardiovascular health, encompassing heart rate, pulse, blood oxygen saturation, and BP. Furthermore, they possess the potential for assessing conditions associated with cardiac output, blood volume, arteriosclerotic or stenotic alterations, and hypertension, showing broad application prospects in the fields of cardiovascular health monitoring.

In the neonatal intensive care unit, continuous vital sign monitoring is essential, however, existing invasive, wired monitoring methods may bring risks of skin damage and infection to newborns. Chung et al. developed a wireless, battery-free vital sign monitoring system that can reconstruct full vital sign information with clinical-level accuracy[154]. The device is mounted on the sole of the foot and records the PPG simultaneously by recording reflected light. The sensor is fully encapsulated from the top, bottom and sides with silicone elastomer, allowing it to function even when completely submerged in water. Tests were conducted on newborns with gestational ages ranging from 28 weeks to 1 month, and SpO_2 was successfully measured using the sensor during rest and breath-holding periods, as shown in Fig. 12a.

Polat et al. demonstrated a new flexible and transparent wearable device based on graphene and semiconductor quantum dot sensitization [49]. The flexible graphene photodetectors demonstrated in this study have excellent photoresponsivity properties; these detectors achieve

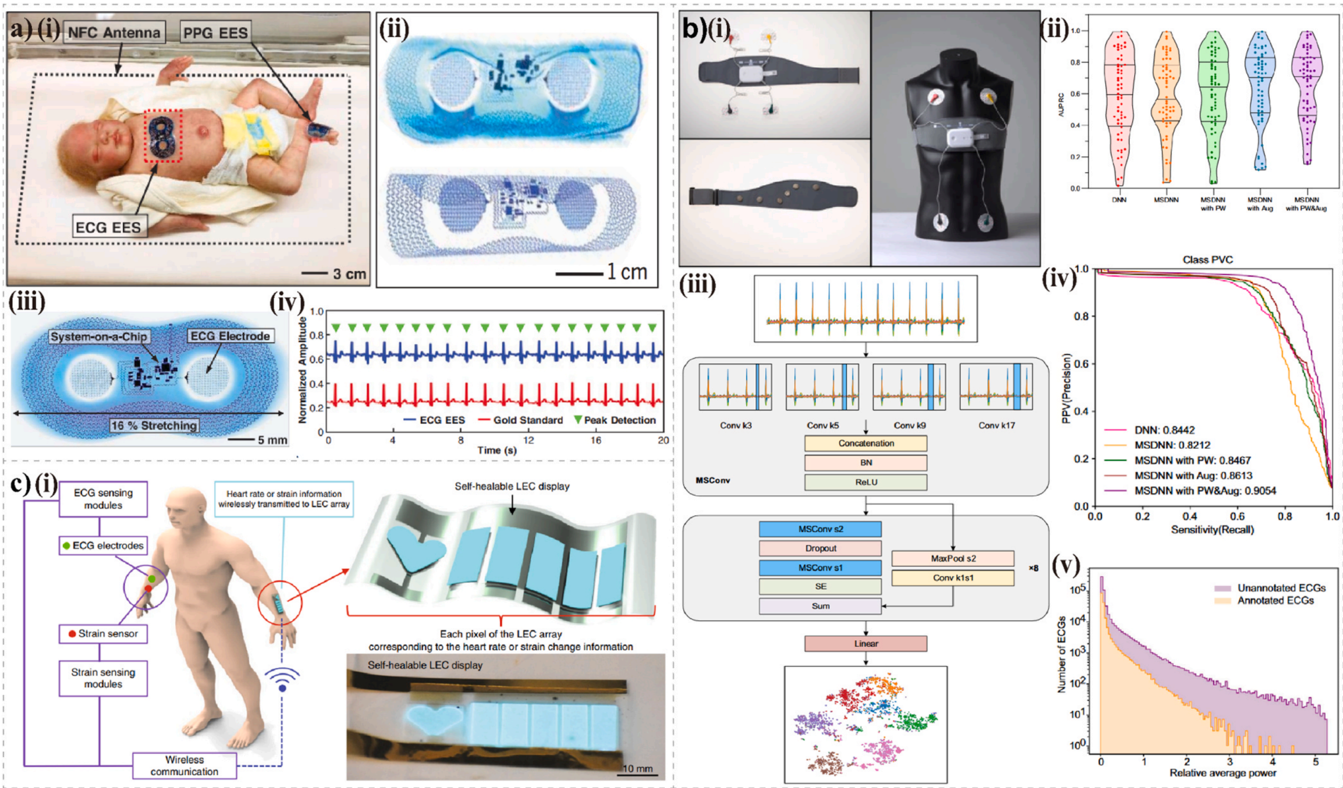

Fig. 13. Wearable ECG sensors. a) A ECG sensor for neonatal health monitoring. (i) Diagram showing the configuration of wireless devices for newborns. (ii) Images and finite-element modeling results for ECG devices bent. (iii) Image of an ECG epidermal electronic system(EES) stretched uniaxially in the horizontal. (iv) ECG signals acquired simultaneously from an ECG EES and a gold standard, with detected peaks. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[154]. b) a self supervised learning classification method for detecting and recognizing ECG diagnostic terms. (i) Wearable ECG device and its standard attachment method. (ii) Ablation study of three strategies. (iii) The architecture of multiscale convolutional network. (iv) Precision-recall curves. (v) Frequency distribution histogram of unannotated ECGs and annotated ECGs on relative average power. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[158]. c) a novel flexible and transparent wearable device based on graphene and semiconductor quantum dot sensitization. (i) Overview of the system with sensors wirelessly communicating values to the display. Reproduced with permission[159], Copyright 2018, Springer Nature.

broad-band sensitivity from 300 to 2000 nm by combining semiconductor quantum dots, and their responsivity can reach levels as high as 10^5 A/W. These properties are made possible by the photoconductor gain in the design, which allows for the separation of bulky readout electronics from the sensor while maintaining the transparency and shape of the sensing area. In addition, these flexible graphene detectors show extremely low power consumption and can operate without the need for an external light source, using ambient light for health monitoring. These key performance parameters make this new sensor particularly promising in the field of wearable cardiovascular health monitoring, enabling effective monitoring of a wide range of vital signs, such as heart rate, oxygen saturation, and respiration rate, as well as battery-free operation of the device and wireless transmission of data, opening up new possibilities for future health tracking devices, as shown in Fig. 12b.

The higher the quality of the PPG signal, the higher the accuracy of the measurement parameters extracted from it. However, PPG signals are susceptible to motion artifacts and baseline drift during the recording process, so Liu et al. used AI technology to assist in classifying the signal quality of PPG[155]. They used two-dimensional deep convolutional neural networks(DCNN) to classify PPG signal quality, and achieved a maximum accuracy of 92.5 % even for those PPG signals severely damaged by motion artifacts and power line interference. This shows that the support of AI technology can help solve the PPG signal quality classification problem faced in the development of wearable devices and promote the application and development of wearable devices in cardiovascular health monitoring, as shown in Fig. 12c. The higher the quality of the PPG signal, the higher the accuracy of the measured parameters extracted from it. However, since PPG signals are susceptible to motion artifacts and baseline drift during recording, signal quality classification becomes critical. Moscato et al. developed two classifiers to identify PPG pulses suitable for heart rate estimation and morphological analysis, achieving the highest performances (accuracies: 96 % and 97 %) using support vector machines, which were superior to existing methods[156]. Automated signal quality assessment methods are essential to improve the reliability of PPG parameters. In addition, Wang et al. evaluated the accuracy and long-term performance of an upper arm cuffless PPG sphygmomanometer using a nonlinear machine learning model architecture and a fine-tuned optimization method [157]. Results showed better signal quality in the upper arm compared to wrist measurements, and the device remained consistently accurate during initial calibration and one-month follow-up. The device does not require frequent calibration, demonstrating its feasibility in long-term continuous BP monitoring and further demonstrating the application of AI techniques in PPG signal quality classification.

Wearable devices based on ECG sensors

With advances in microelectronics and the use of high-performance materials, modern ECG sensors have evolved into more compact and sensitive devices that seamlessly integrate with wearable technology to provide continuous ECG monitoring around the clock. These devices are not only small in size, but also highly flexible and malleable, allowing them to fit snugly against the skin and reducing discomfort while

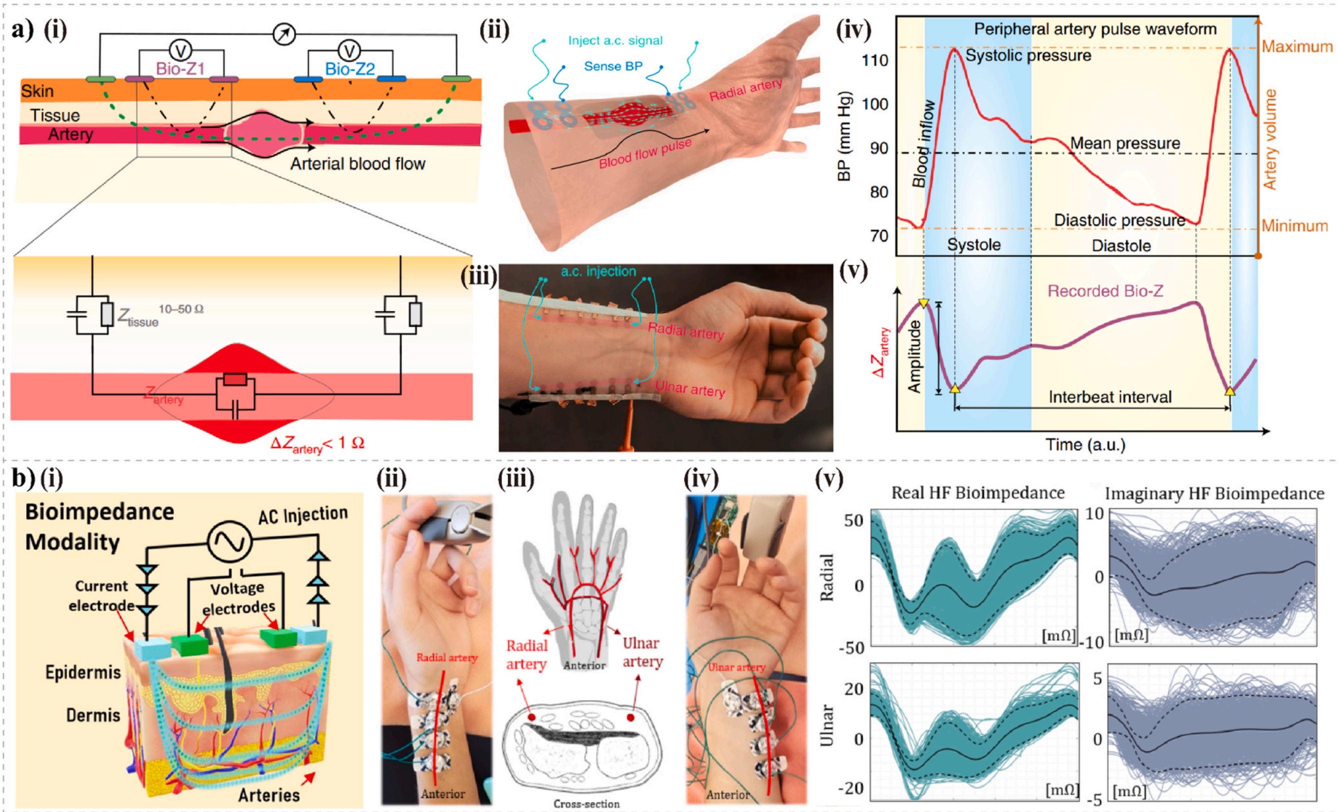

Fig. 14. Wearable BIA sensors. a) A wearable BP monitoring platform based on graphene electronic tattoos. (i) Close-up view of six graphene electronic tattoos (GETs) and simplified equivalent circuit of a pair of sensing GETs interface. (ii) Three-dimensional schematic diagram of GETs placed in the radial artery of the subject's wrist. (iii) Photograph of 12 GETs placed in the radial and ulnar arteries of the subject's wrist. (iv) Illustration of the peripheral arterial BP pulse waveform and correlated arterial volume. (v) The BIA signal is reciprocal to the BP pulse waveform. Reproduced with permission [162], Copyright 2018, Springer Nature. b) Monitoring different parts of the human body to obtain multiple cardiovascular parameters. (i) Schematic diagram of bioimpedance modality testing. (ii), (iv) Electrodes placed on the radial artery (left) and ulnar artery (right). (iii) Transverse section of the wrist showing the location of the radial and ulnar arteries. (v) Real and imaginary total high-frequency bioimpedance signals obtained from the radial and ulnar arteries. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[163].

maintaining signal accuracy and reliability. The integration of AI further enhances the functionality of these ECG devices, allowing them to not only capture ECG signals, but also analyze the data in real-time through sophisticated algorithms to automatically identify abnormal activities such as arrhythmia, tachycardia or bradycardia. Additionally, AI technologies can learn from large amounts of accumulated data to improve the accuracy of predicting cardiac events, thus providing critical early warnings in emergency situations. Taken together, these technological developments have not only improved the ease and comfort of use of ECG devices, but have also enhanced the real-time and predictive nature of cardiovascular health monitoring, bringing significant health management benefits to both providers and patients.

In the process of continuous vital sign monitoring of newborns, Chung et al. demonstrated a wireless and battery-free ECG monitoring system that can collect physiological signals with clinical-level accuracy [154]. The system features high mechanical compliance and a non-invasive skin-adhesive interface, and is well compatible with traditional ECG examinations. By eliminating wired connections, the system promotes therapeutic skin-to-skin contact between newborns and parents, stabilizing vital signs. In addition, the system also has functions such as multi-point temperature sensing and BP tracking, which can provide more dimensions of cardiovascular health-related information, as shown in Fig. 13a.

AI plays an increasingly important role in intelligent diagnosis of ECG, and the improvement of diagnostic accuracy depends on the input of large amounts of data. Lai et al. used a wearable 12-lead ECG collection device to collect ECG data from 658,486 test subjects[158]. About 25 % of the data is labeled, and the remaining 75 % is undiagnosed data. They use self-supervised learning to mine the information contained in large amounts of ECGs and transfer the learned knowledge to classification tasks to improve generalization capabilities. Implemented a self-supervised learning classification method that can detect and identify 60 ECG diagnostic terms, including sinus rhythm, arrhythmia, and heartbeat waveform changes, as shown in Fig. 13b.

In the ECG acquisition process, the quality of the electrodes often determines the quality of the signal. During the collection process, slight movement or shaking of the body is inevitable, so the stretchability and self-healing ability of the electrode are very important. Son et al. proposed a dynamically reconfigurable conductive nanonetwork[159]. The fractured part of the nanoconductive network encapsulated in a self-healing polymer matrix can autonomously heal with the dynamic reconstruction of the self-healing polymer. This autonomous healing enables the nanoconductive network to not only restore its high conductivity, but also restore its mechanical properties. In self-healing airborne systems, utilizing the self adhesive properties of self-healing polymers, ECG sensors and other components can be seamlessly integrated into one platform to achieve detection of ECG signals. In addition, the physiological data recorded by each sensor can be wirelessly transmitted to the light-emitting capacitor array to provide real-time continuous monitoring. This makes it possible to manufacture various stretchable and self-healing wearable devices for cardiovascular health monitoring, as shown in Fig. 13c. Furthermore, Chen et al. developed an automatic atrial fibrillation detection method tailored for wearable devices, employing deep learning techniques[160]. The approach involves

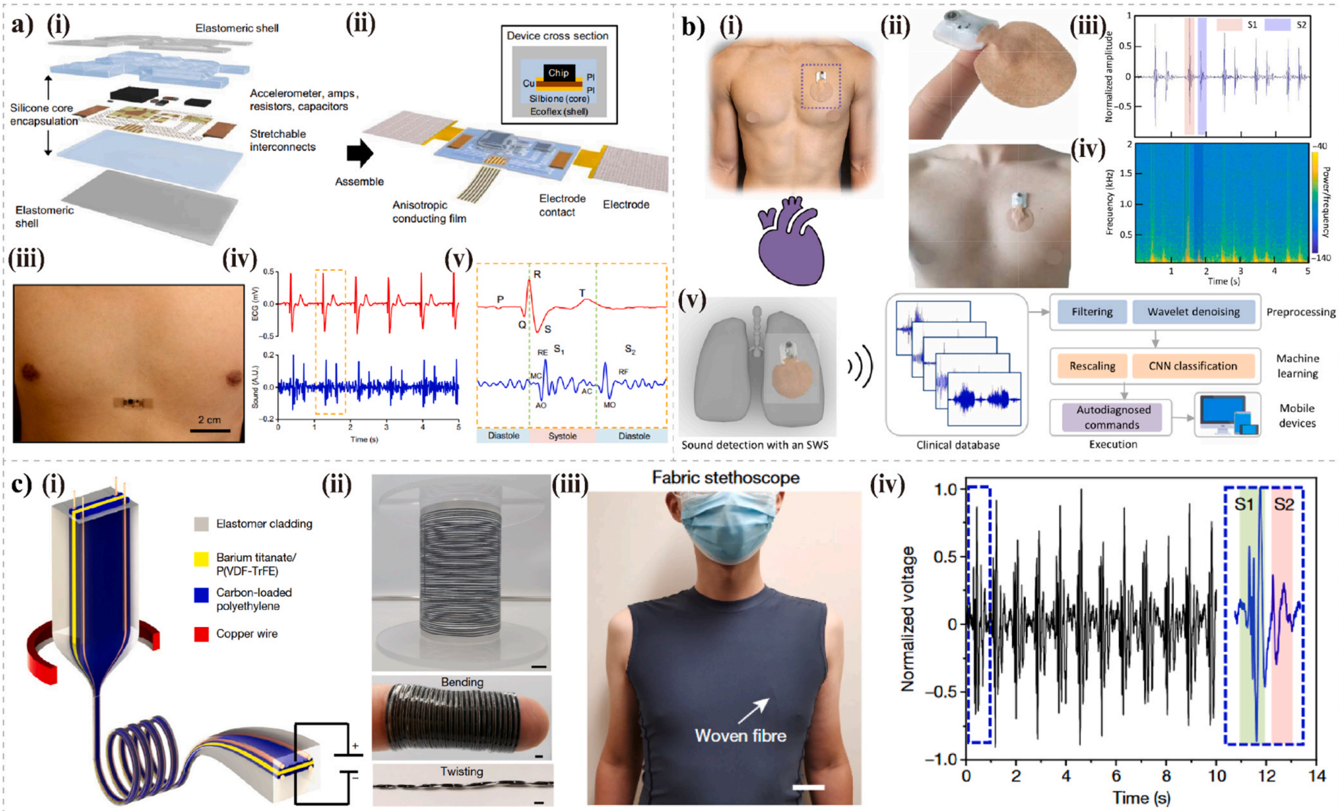

Fig. 15. Wearable SCG/BCG sensors. a) A mechanical acoustic electrophysiological sensing platform is used to record mechanical sounds from the body. (i) Exploded view of the overall structure. (ii) Schematic diagram of the assembled device. (iii) Image of an epidermal device mounted on the chest. (iv) Simultaneous measurement of ECG and heart sound signals. (v) ECG and heart sound signals in enlarged view. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[166]. b) A wireless, real-time, continuous wearable auscultation system for heart and lung diagnosis. (i) Photo of the SWS mounted on the chest for heart sound detection. (ii) Enlarged photo of the device on the fingers and chest. (iii) Time-series plot of the 5-s window heart sounds, measured from a healthy subject. (iv) Spectrogram of the time series graph. (v) Schematic illustration of the flow for automated, objective diagnosis of diseases via machine learning in the SWS. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[167]. c) A novel fabric for detecting cardiac mechanical sounds. (i) Schematic of preform-to-fiber thermal drawing and fiber poling. (ii) Photos of fiber winding and bending. (iii) Practical application of the fabric stethoscope. (iv) Signal diagram of the measured heart rate and heart sounds. Reproduced with permission[168], Copyright 2022, Springer Nature.

novel preprocessing steps, including wavelet transform and sliding window filtering, to reduce noise and outliers in ECG signals. A robust R-wave detection algorithm was implemented, achieving a detection sensitivity of 99.22 % and a positive recognition rate of 98.55 % on the MIT-BIH arrhythmia database. The proposed feedforward neural network for atrial fibrillation detection demonstrated an accuracy of 84.00 %, a sensitivity of 84.26 %, and a specificity of 93.23 % on a mixed dataset from the Challenge2017 and MIT-BIH databases. These results underscore the potential of this method for early atrial fibrillation prediction in wearable applications. ECG is also a key tool for the diagnosis of myocardial infarction, but the application of deep learning methods is limited by privacy issues and insufficient data, especially the lack of support for single-lead ECG data. To solve this problem, Li et al. proposed the SLC-GAN model, which synthesizes single-lead ECG data with high morphological similarity by generative adversarial network and combines it with convolutional neural network to automatically detect myocardial infarction, and the experiments show that this method can classify myocardial infarction on single-lead ECG with an accuracy of 99.06 %[161].

Wearable devices based on BIA sensors

Technological advances in BIA have focused on improving measurement accuracy and portability to meet the growing demand for home health monitoring and telemedicine. By integrating advanced sensors and microprocessors, the latest BIA devices are able to more accurately measure and analyze the body's water and electrolyte balance, which is particularly critical for assessing cardiovascular health. For example, modern BIA devices are able to take measurements at different frequencies to discern the distribution of fluids inside and outside of cells, which helps to provide a more nuanced understanding of the load on the cardiovascular system. Additionally, these devices are often equipped with wireless transmission capabilities, enabling real-time data transfer to a smartphone or healthcare app to support ongoing health tracking and data analysis. This wireless capability makes BIA technology particularly important in the field of continuous cardiovascular monitoring, as it allows physicians to remotely monitor a patient's hydration status and cardiovascular health and make timely adjustments to treatment plans. Recent applied research has shown that BIA devices not only assess body composition, but can also be used to monitor circulation and cardiac health indicators such as cardiac output and cardiovascular reactivity. The monitoring of these indicators can help predict the risk of CVDs and provide important information in daily health management. Through the integration and application of these technologies, BIA has become a versatile diagnostic tool that can be used in a wide range of clinical and home settings.

Kireev et al. reported a BIA-based wearable continuous BP monitoring platform that utilizes graphene electronic tattoos as a bioelectronic interface[162]. Due to the self-adhesive and low impedance characteristics of graphene electronic tattoos, even with time and body movement, the electronic tattoos are always in the same position on the skin. Therefore, the evaluation model is determined from the beginning. There is no need to repeatedly recalibrate the model with electrode misalignment or sensor movement like other wearable electrode types. Graphene electronic tattoos can be used to monitor arterial BP for over 300 minutes, achieving continuous non-invasive high-precision recording of BP. The accuracy of diastolic BP is 0.2 ± 4.5 mm Hg, and the accuracy of systolic BP is 0.2 ± 5.8 mm Hg, as shown in Fig. 14a.

Due to the lack of specific detection locations, BIA can detect various parts of the body. Sel et al. conducted a comprehensive analysis of different arteries (ulnar artery, radial artery, tibial artery, and carotid artery) and chest (intercostal fusion cage and thoracolumbar fascia) [163]. Overall, the average errors in estimating the heartbeat interval and breathing interval are as low as 0.003 ± 0.002 and 0.67 ± 0.28 seconds, respectively. The results indicate that BIA can be effectively used to monitor important cardiovascular parameters in multiple parts of the human body, including blood flow, lung movement, muscle contraction, and fluid movement, as shown in Fig. 14b. Chiu et al. applied an artificial neural network to estimate total body water in hemodialysis patients, improving upon traditional anthropometric methods[164]. The approach closely matched multifrequency bioelectrical impedance analysis results, highlighting AI's potential to enhance precision in patient monitoring. Similarly, Nana et al. utilized two-dimensional smartphone images for body composition analysis, comparing it with traditional methods in 929 adults[165]. Their AI-based technique demonstrated strong agreement with dual-energy X-ray absorptiometry and outperformed bioelectrical impedance analysis, underscoring the role of AI in providing accessible, accurate assessments for cardiovascular health monitoring through wearable and mobile technologies.

Wearable devices based on SCG/BCG sensors

The technological advancements in SCG and BCG sensors are mainly characterized by their improved sensitivity and signal processing capabilities, as well as enhanced user portability and wearing comfort. These devices are fabricated through microelectromechanical system technology, enabling them to accurately capture the minute mechanical vibrations caused by cardiac activity. The integration of SCG and BCG devices allows them to be seamlessly embedded into wearables and everyday items, such as smartwatches and health-monitoring bracelets, to enable continuous monitoring of cardiac mechanical activity. In cardiovascular health monitoring, SCG and BCG devices effectively monitor heart pumping efficiency and cardiac pathology, providing critical data for early diagnosis and treatment of heart disease. When used in conjunction with ECG, these devices provide a more comprehensive assessment of cardiovascular health. Next-generation acoustic sensors are increasingly using AI algorithms to improve the accuracy of data analysis, helping to identify abnormal rhythms and potential cardiovascular problems in real-time, enabling early intervention. The integration of this technology extends the promise of SCG and BCG for CVDs monitoring.

The mechanical sound electrophysiological sensing platform developed by Liu et al. utilizes the latest in stretchable electronics to achieve soft, well-compliant integration with the skin[166]. Designed for mechanical sound recordings from virtually any part of the skin, this platform's features include a low effective modulus and low area mass density, which are key to operating effectively in this measurement mode. The device is only 2 mm thick and has very low bending stiffness, allowing it to fit almost seamlessly into any area of the body, including the curved portion of the neck, to capture signals related to breathing, swallowing, and vocalization. The platform has shown its utility in a number of applications, including cardiovascular diagnostics and human-machine interfaces. For example, in cardiac patients, it successfully recorded heart murmurs and vibratory sounds of blood-pumping machinery, demonstrating its utility in clinical diagnostics. In addition, the device can monitor pumping machinery malfunctions in ventricular assist devices and detect thrombosis or drive failures in pumping machinery by capturing the vibro-acoustic signature of these devices, which is particularly important in cardiac therapeutic device monitoring. This wearable acoustic sensing platform provides a new and efficient means of cardiovascular health monitoring through its highly integrated sensor and circuit design and its ability to record multiple physiological signals simultaneously, as shown in Fig. 15a.

The study by Lee et al. describes a soft wearable stethoscope system that accurately performs cardiopulmonary auscultation during daily activities by utilizing electronic and flexible mechanical technologies [167]. This system significantly optimizes the bulky size and friction noise issues associated with conventional and digital stethoscopes for continuous monitoring. The soft wearable stethoscope (SWS) device uses a microelectromechanical system of microphones and advanced signal processing to improve signal-to-noise ratios, achieves close contact with the skin through a soft material design, and reduces noise interference caused by motion. In addition, the wearable stethoscope system has a built-in machine learning model that automatically diagnoses lung diseases including lung crackles, wheezing, tension and breathing sounds with up to 95 % diagnostic accuracy. Its mobile device app tracks and displays signals in real-time, automatically diagnoses a wide range of abnormal lung sounds, and securely uploads the information to local storage. This new stethoscope shows promising applications for early detection and continuous monitoring of cardiopulmonary diseases due to its portability, high sound quality recording capability and potential for automated disease diagnosis, as shown in Fig. 15b.

Yan et al. invented a fabric that retains the machine washing and drape properties of traditional fabrics while also serving as a sensitive microphone for detecting cardiac mechanical sounds[168]. Due to its high sensitivity to vibration and impedance matching with the skin, this fabric can be used for cardiac auscultation and as a basic tool for diagnosing CVDs. A subject wearing an acoustic shirt made of this fabric can clearly detect high-quality heart sounds, including strong S1 and weak S2, with a signal-to-noise ratio of up to 30 dB. It functions as a skin interface stethoscope, providing a long-term and comfortable solution for real-time monitoring of heart and respiratory conditions, and subsequently diagnosing cardiovascular health, as shown in Fig. 15c. Shandhi et al. applied machine learning to wearable SCG signals to estimate pulmonary pressures in heart failure patients, aiming to address the variability in traditional methods[169]. They used 500 ms SCG segments around ECG R-peaks to represent systolic and diastolic phases, simplifying feature extraction and avoiding the challenges of identifying valve opening and closing points, which are often inconsistent across individuals. By employing ensemble averaging and general feature extraction, their method effectively estimated pressure changes with high accuracy, showcasing the potential of AI-driven wearable technology for reliable, non-invasive monitoring of heart failure patients.

Wearable devices based on ultrasonography sensors

With advances in transducer technology, a new generation of ultrasound devices has achieved greater flexibility, miniaturization, and arraying, enabling more accurate deep tissue monitoring of the cardiovascular system. The core technologies of these ultrasound devices include highly sensitive miniaturized transducers and highly integrated electronic systems, enabling the devices to provide not only real-time hemodynamic data, but also more in-depth physiological and pathological analyses through advanced image and signal processing algorithms. For example, flexible ultrasound devices can fit snugly against the skin and transmit data in real-time via wireless technology, which is particularly important in monitoring heart health over time and predicting CVDs. In terms of applications, these devices are able to provide predictive information on all-cause CVDs mortality by continuously monitoring BP waveforms in blood vessels, which is clinically valuable

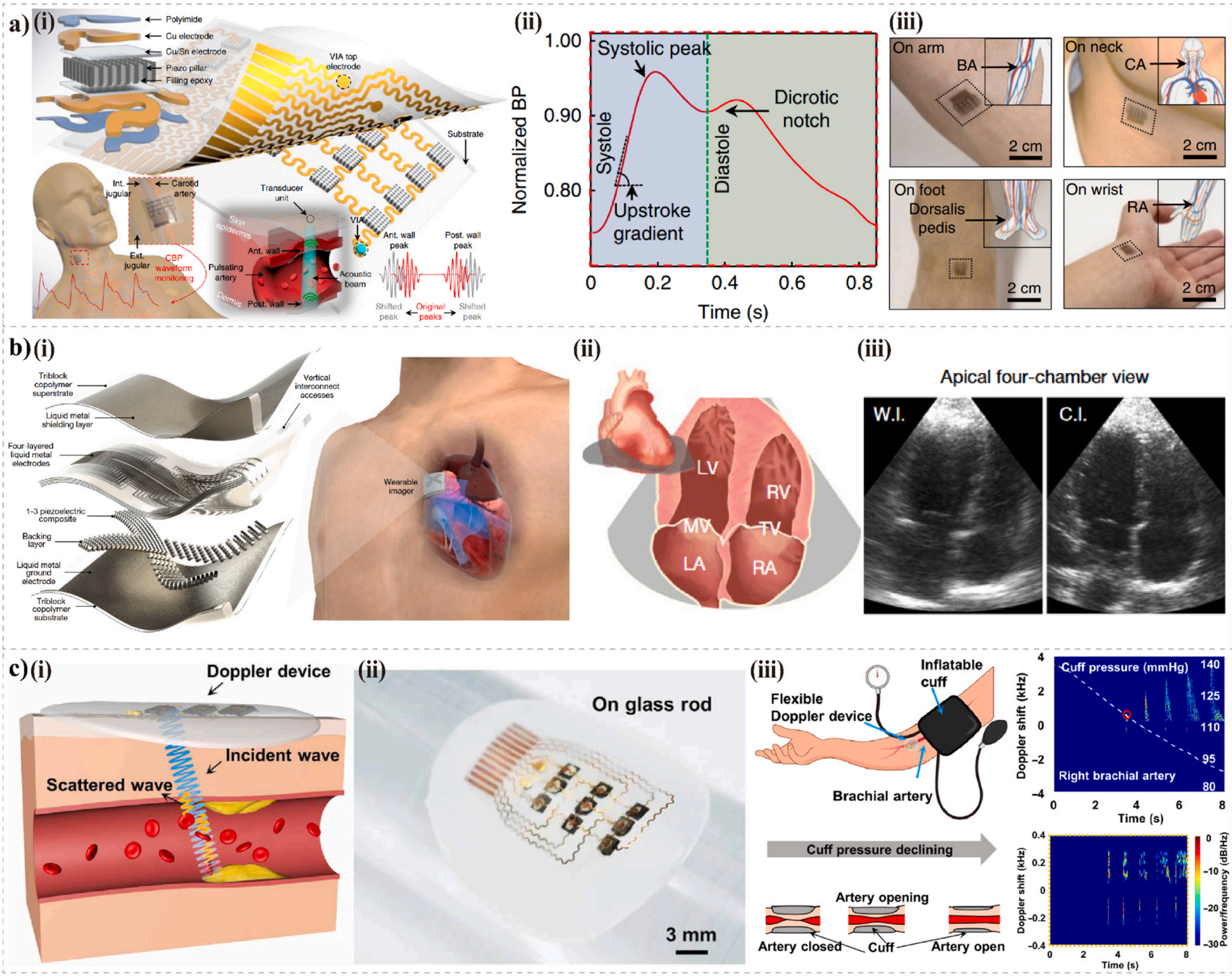

Fig. 16. Wearable ultrasonic sensors. a) Stretchable ultrasound device for monitoring neck BP. (i) Schematic diagram of the stretchable ultrasound device. (ii) A typical pulse waveform measured from the carotid artery. (iii) BP measurement from the central artery to the peripheral artery. Reproduced with permission[96], Copyright 2018, Springer Nature. b) Wearable ultrasound imager for continuous and real-time cardiac function evaluation. (i) Exploded view of the wearable imaging device. (ii) Schematic diagram of the heart anatomy. (iii) Ultrasound images from wearable and commercial imagers. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[95]. c) Flexible ultrasound device for real-time and continuous monitoring of absolute blood flow velocity. (i) Schematic diagram of a Doppler ultrasound device. (ii) Optical image of the device bending around a curved surface. (iii) Schematic diagram of a measuring device and a Doppler spectrum of the brachial artery. Reproduced according to the terms of the CC-BY Creative Commons Attribution 4.0 International license[94].

for early diagnosis and intervention in CVDs.

The study by Wang et al. reports an innovative stretchable ultrasound device whose main feature is the ability to perform noninvasive, continuous and accurate monitoring of BP waveforms in deeply buried arteries and veins of the neck[96]. The advantages of this device over conventional methods are its stretchability (up to 60 % strain) and thinness (240 μm thick), which allows it to fit snugly into the skin and work effectively even in deep tissues. The device is made of a 1–3 piezoelectric composite material and has an operating frequency of 7.5 MHz and an axial resolution of 400 μm, performance indicators that guarantee its efficiency and precision in monitoring cardiovascular events. With this technology, cardiovascular activity can be captured from multiple body locations, significantly enhancing the potential for applications in clinical settings, as shown in Fig. 16a.

Continuous imaging of cardiac function is essential for evaluating long-term cardiovascular health. However, traditional equipment cannot maintain continuous and long-term testing due to its large size. Hu et al. reported a wearable ultrasound imager for continuous, real-time cardiac function assessment[95]. This device improves the mechanical coupling between the device and the human skin, allowing the left ventricle to be examined from different angles during movement. Even if the subjects are engaged in high-intensity exercise, uninterrupted frame by frame heart image acquisition can still be performed. In addition, the wearable ultrasound imager also integrates a deep learning model, which can automatically extract left ventricular volume from continuous image records, and obtain waveforms of key cardiac performance indicators such as stroke output, cardiac output, and ejection fraction. This technology enables dynamic wearable monitoring of cardiac performance in various environments and has potential application value in areas such as intensive care and CVDs management, as shown in Fig. 16b.

A flexible continuous-wave Doppler ultrasound device developed by Wang et al. enables real-time continuous monitoring of blood flow velocity by means of a transducer array made of 1–3 piezoelectric composite material[94]. The device utilizes a dual-beam Doppler method that effectively avoids the effects of Doppler angle and accurately

Table 2
Comparison of wearable device materials, performance and applications.

Principle	Sensing Material/ Components	Electrode Material	Structural Material	Form	Key Indicators	Detection Area	Application	References
Active pulse pressure sensors	Polyurethane-based nanofibers	Pt	PDMS	Patch	Sensitivity GF~11.45	Radial artery	Heartbeat monitoring	[145]
	Carbonized silk georgette	nickel fabric	Ecoflex	Patch	Sensitivity GF~9.81	Radial artery	BP and heart function parameter monitoring	[106]
	PEN	Cr/Au	PVA	Patch	Sensitivity 0.55–0.58 kPa^{-1}	Radial artery/ Carotid artery	deep-lying internal jugular venous pulses monitoring	[147]
Passive pulse pressure sensors	PVDF	Ag	PTFE	Wristband	Signal-to-noise ratio of 29.7 dB	Radial artery	BP monitoring	[149]
	Cardboard/Silicone rubber	Cu	insulating fabric	Wristband	Sensitivity 0.89 V/ kPa	Radial artery	BP monitoring	[150]
	Magnetic induction/ giant magneto mechanical coupling	Cu	-	Wristband	Sensitivity 10^{-8} T/ Pa	Radial artery/ Brachial artery	Wearable/ implantable device power supply/pulse monitoring	[152]
Photoplethysmography	Red/IR LED Photodetector	Cu	silicone elastomer/ PDMS	Patch	Single-axis elongation 13 %	Sole of foot	Heart rate/blood oxygen monitoring	[154]
	Graphene sensitized with semiconducting quantum dots	Ti/Au	PEN	Patch	Responsivity 10^5 A/W	Fingertips/ Arms	Heart rate/blood oxygen monitoring/ ultraviolet detection	[49]
Electrocardiogram	Ionic liquid and silica gel	Cu	silicone elastomer/ PDMS	Patch	Single-axis elongation 16 %	Chest	Pulse arrival time monitoring	[154]
	PDMS–MPU0.4–IU0.6	AgNW	-	Patch	Strain 50 %	Arms	Continuous wireless monitoring of heart condition	[159]
Bioimpedance Analysis	Graphene	Graphene	-	Tattoo	Accuracy 1 mΩ	Arms/ Neck/Legs	Continuous cuffless monitoring of arterial BP	[162]
Seismocardiography/ Ballistocardiography	Accelerometer	Cu	PI/Ecoflex	Patch	Bending stiffnesses 0.94 Mn·m (in the y direction)	Chest/ Neck/Arms	Cardiac valvular stenosis monitoring	[166]
	MEMS mic	Cu	Silicone elastomer	Patch	Signal-to-noise ratio of 14.8 dB	Chest	Cardiopulmonary monitoring	[167]
Ultrasonography	Lead zirconate titanate	Cu/Sn	PI	Patch	Piezoelectricity k33 up to 0.81	Neck	Monitoring of the central BP	[96]
	1–3 piezoelectric composite	gallium–indium liquid metal	SEBS	Patch	Centre resonant frequency of 3 MHz	Chest	Continuous imaging of cardiac functions	[95]

Abbreviations: Polydimethylsiloxane (PDMS), Polyvinyl alcohol (PVA), Polytetrafluoroethylene (PTFE), Polyethylene naphthalate (PEN), 4,4'-methylenebis(phenyl urea) unit (MPU), Isophorone bisurea unit (IU), Silver nanowires (AgNW), Carbon nanotubes (CNTs), Polyimide (PI), Styrene ethylene butylene styrene (SEBS).

measures blood flow velocity without calibration. The device's flexible and lightweight design allows it to fit snugly against the skin for improved comfort. Compared to conventional ultrasound devices, the device is easy to operate and does not require an experienced operator. It operates at a frequency of 5 MHz and has a detection depth of up to 25 mm, which meets the need for deep vascular monitoring. The device confirms its excellent blood flow velocity monitoring capability, showing promise for a wide range of applications in clinical and home health monitoring, as shown in Fig. 16c.

Advancements in AI have increasingly impacted ultrasound imaging research, particularly in enhancing diagnostic capabilities. Yan et al. demonstrated a trans-thoracic ultrasound localization microscope for imaging myocardial microvascular systems and hemodynamics[170]. This method overcomes challenges in visualizing small, moving microvessels in the heart by utilizing gas-filled microbubbles to achieve super-resolution imaging. The technique effectively captures detailed images of myocardial blood flow and vascular structures, even during breath-holding in patients with impaired myocardial function, offering a promising non-invasive tool for advanced cardiovascular imaging. Xiao et al. introduced a novel deep learning approach for tracking arterial wall displacement from ultrasound radiofrequency signals, addressing the need for early monitoring of arterial mechanics related to CVDs [171]. This deep learning-based method demonstrates higher accuracy in tracking arterial wall motion compared to traditional methods, as shown by carotid artery simulation and experimental data. Unlike conventional speckle tracking, which analyzes current data in isolation, this deep learning technique leverages both amplitude and phase information from radiofrequency signals, enhancing its capability to quantify vascular biomechanics and predict early cardiovascular pathology.

Comparison of materials, performance and application of emerging in intelligent wearable devices

In wearable devices, the choice of materials directly affects their performance and application scenarios. Here we have made a detailed summary of the sensing material, electrode material, structural material, form, performance, detection area and practical application of various wearable devices, as shown in Table 2. For pulse pressure sensors, the sensitivity and responsiveness to pressure are mainly concerned. Therefore, sensing materials with high pressure responsiveness are sought, such as piezoelectric materials with high electromechanical coupling coefficient and triboelectric materials with high electron affinity[172]. These materials are very suitable for monitoring weak pulse signals because of their high sensitivity and response speed. PPG sensors pay more attention to light responsiveness, so the sensing material emphasizes photoelectric conversion efficiency. For example, graphene sensitized with semiconducting quantum dots is used to capture the weak light change signal in blood oxygen monitoring. ECG sensors focus on biocompatibility and signal stability, and usually select sensing and electrode materials with high conductivity and extensibility, such as ionic liquids and silver nanowires, combined with silicone rubber encapsulation, to ensure long-term stable ECG signal monitoring. The key to the design of BIA sensors is high conductivity and skin adhesion. The electrodes made of graphene materials not only have excellent conductivity, but also can be in close contact with the skin to achieve high-precision bioimpedance measurement, suitable for arterial BP monitoring, and can be applied to the arms, neck, and legs in the form of electronic tattoo. SCG and BCG sensors emphasize sensitivity and miniaturization, using accelerometers and MEMS microphones, combined with PI and silicone rubber encapsulation, making them suitable for heart valve stenosis and cardiopulmonary function monitoring in patch form on chest. Ultrasonography sensors rely on high piezoelectric coefficients and frequency response, and are usually made of PZT piezoelectric composite materials to achieve high-precision continuous imaging of central BP and cardiac function. Most of wearable devices are in the form of patches, which can be comfortably attached to the skin and are suitable for a variety of monitoring sites, such as the wrist, arm, chest, neck and leg. By selecting and optimizing different materials combination, the performance and applicability of various sensors have been significantly improved, promoting the widespread use of wearable devices in the field of cardiovascular health monitoring.

With the development of smart wearable devices, traditional material design faces many challenges, such as the difficulty of predicting material properties and long design cycles. In the latest developments, AI can play a significant role in the initial design of sensors, such as by guiding the microstructure design of sensing materials to achieve performance optimization[173–177]. Traditional material design methods often rely on trial and error and simulation, which is time-consuming and resource intensive[178,179]. The introduction of AI technology can greatly improve design efficiency. For example, a key challenge in the design of flexible pulse pressure sensors is to achieve a linear response over a wide pressure range. AI can be used to generate material structures that meet the target characteristics through data-driven reverse design methods, thereby achieving better performance on a variety of materials[180]. By combining the advantages of AI technology and material science, future smart wearable devices will achieve further breakthroughs in performance and application range. The introduction of AI not only solves bottlenecks in existing technologies, but also opens up new directions for new materials and sensor designs, promoting the intelligent development of cardiovascular health monitoring.

Conclusion and outlook

In this review, we focus on discussing six major CVDs indicator signals and their detection methods and show examples of applications where AI has been combined with these technologies. In the future, intelligent wearable devices designed for cardiovascular health monitoring will be more integrated, systematic, smarter, and functionally diverse. They may employ electronic skin, electronic textiles, and other mediums as carriers, forming a body area network of signals and energy in conjunction with commonly used wearable devices such as wristbands. The realization of these functions depends on the seamless integration of sensor components, signal acquisition, processing and transmission circuits, computational units, cloud platforms, as well as standardized clinical procedures and protocols, which is a systemic engineering endeavor. Ergonomically designed to integrate high-speed, high-precision ADCs, high-capacity batteries, low-power MCUs, Bluetooth 6.0, and AI technologies, the aim is to establish a multimodal data collection and multi-signal wireless transmission system. This will facilitate the development of a new generation of intelligent wearable devices, enhancing their accuracy, efficiency, comfort, and convenience for cardiovascular health monitoring. However, to achieve the above goals, current smart wearable devices still face important challenges, such as miniaturization, flexibility, accuracy, intelligence, user comfort, privacy, etc. Here, we summarize and look forward to the four aspects of device design, algorithm optimization, comfort reliability, and security.

Device design

When designing a wearable device, to ensure that the device meets the functional requirements and to optimize the user experience and device performance, we need to consider all four key aspects: Material design, Structural design, Energy management and Sensing technology.

The choice of materials is crucial for improving the performance of sensors, directly affecting the sensitivity, response speed and stability of the device. Advanced materials such as graphene and liquid metal can enhance the quality and stability of signal transmission due to their excellent electrical conductivity and mechanical flexibility, thereby improving the accuracy of detection of biological signals such as ECG. Sensing materials with surface microstructure can significantly improve the sensing performance by increasing local stress or increasing the contact area. The choice of high-strength materials such as carbon fiber composites significantly improves the durability and service life of the device. The use of waterproof and dustproof materials such as PTFE and PI can effectively protect the internal electronic components and ensure the normal operation of the device in various environments. The use of flexible, stretchable and skin-friendly materials such as silicone elastomers and hydrogels ensures long-term wearing comfort and the stability of the device under activities. Breathable materials such as fabric electrode can reduce heat build-up on the skin and improve the user experience. Overall, by optimizing material design, wearable sensors have greatly improved in terms of performance, comfort and durability, meeting the diverse needs of cardiovascular health monitoring. In the future, with the continuous advancement of materials science, wearable devices will become smarter and more versatile. For example, self-healing materials can automatically repair damage and extend the service life of sensors. Smart response materials can adjust themselves according to changes in the external environment, improving the adaptability and reliability of the device. The research and application of conductive polymers will provide sensors with better flexibility and conductivity. Innovations in biocompatible materials will boost the safety and comfort of long-term wear.

In the structural design of wearable devices, physical layout, component integration, and mechanical stability are prioritized design factors for smart wearable devices. Optimizing the physical layout is critical to ensure that electronic components such as sensors, batteries, and processors are properly configured to maintain the compactness and lightweight nature of the device. In addition, component integration requires highly integrated circuitry and modular design to optimize device functionality and user experience. Integrating functional components into a stacked multilayer design can effectively address the limitations of traditional single-layer design in terms of functional density[181–183]. MEMS have the advantages of small size, light weight, low cost, low power consumption, and high reliability, which greatly contribute to the miniaturization of wearable devices. Mechanical stability is also critical to ensure the durability and long-term integrity of the device during daily activities. With these integrated structural design considerations, wearable devices not only provide sustained performance, but also maintain maximum user comfort and satisfaction.

In terms of energy management, although the batteries of wearable devices have taken up a large portion of the overall system space, to achieve the goal of long-term continuous monitoring, the current battery capacity is still very limited, so it is necessary to further reduce the overall power consumption of the system. The first step can be to optimize the hardware design, such as choosing MCUs with lower power consumption or using self-driven sensors such as triboelectric sensors and piezoelectric sensors to reduce the power consumption of the sensing unit. On the other hand, optimization can be done in terms of software design, such as reducing back-end data transmission and limiting network connections, which are also important strategies for improving energy efficiency. In conclusion, energy management of wearable devices requires comprehensive consideration of multiple factors such as hardware, software and user interaction to extend the usage time of the device and provide a better user experience.

In the design of sensing technologies for wearable devices, the selection and optimization of sensors is key to improving the efficiency and functionality of the devices[184]. In particular, it is important to select self-driven or energy-harvesting sensors such as triboelectric sensors and piezoelectric sensors, which generate electrical energy while collecting data, thereby reducing the overall device energy consumption. These types of sensors utilize the user's daily activities (e.g., walking, running) to generate energy, which not only reduces reliance on traditional batteries, but also increases the device's uptime and independence. By directly converting mechanical energy into electrical energy, this self-driven sensing technology provides an efficient way to continuously monitor a user's physiological state without consuming additional power. In addition, the integration of these sensors requires precise design and layout to ensure their effectiveness and sensitivity in the device while keeping it lightweight and comfortable. By utilizing advanced micromachining techniques, these sensors can be designed to be extremely tiny and efficient for long-wearing application scenarios.

Algorithm optimization

Algorithm optimization is a crucial aspect in the design of AI-based wearable devices, with the main purpose of improving the processing efficiency of the devices, reducing power consumption, and coping with the need to process massive amounts of data. Effective algorithm optimization can significantly improve the performance of the device, making it more accurate and efficient in real-time analysis of complex ECG signals and detection of CVDs.

First, optimizing algorithms mainly involves improving data processing speed and accuracy. For example, by introducing efficient data compression and preprocessing techniques, the amount of data that the device needs to process and transmit can be reduced, resulting in lower energy consumption and longer battery life. In addition, the use of advanced machine learning models such as convolutional neural networks and recurrent neural networks can improve the ability to classify and analyze biosignal.

Wearable devices are able to collect richer and more diverse data than traditional medical means through continuous and real-time monitoring. This 24/7 data collection significantly increases the amount of data and provides more training samples for machine learning models, which improves the learning effectiveness and predictive power of algorithms. For example, in CVDs monitoring, data recorded continuously through ECG and activity monitoring sensors can be used to train algorithms to identify heart rhythm abnormalities and assess cardiovascular health status[185]. The addition of this data not only optimizes the algorithm's ability to recognize complex patterns, but also enhances the algorithm's adaptability and accuracy in diverse and uncontrolled environments. Additionally, data collected by wearables has a higher degree of life fit and physiological response in natural states, which is especially critical for studying how physiological states change in everyday environments. For example, in CVDs monitoring, where traditional ECG tests may not be able to capture changes in a patient's heart rate under specific life stressors, wearables can record this critical data, opening up possibilities for early diagnosis and personalized treatment. This data from everyday life increases diagnostic accuracy and provides a new perspective on disease management.

In addition, by integrating and applying deep learning techniques such as Generative Adversarial Networks, the scope of data augmentation can be further extended and the generalization ability of the models can be improved. The application of these techniques is not limited to data augmentation, but also includes automatic feature extraction and anomaly detection, which are key factors in improving algorithm optimization and device performance[186–188].

In conclusion, algorithm optimization plays a decisive role in improving the core competitiveness of AI-based wearable devices. Through targeted continuous learning and iteration, wearable devices based on AI can perform personalized data analysis and prediction according to different individual situations. By collecting and analyzing user biological data, devices can provide accurate assessment of cardiovascular health status and provide targeted recommendations and solutions based on individual needs. In addition, a universal AI based on large models can also be established, which can seamlessly integrate with other intelligent devices and medical systems. The device can be connected to the systems of hospitals, clinics, and other medical institutions, and can interact and share data with other medical devices and databases. This integration enhances diagnostic accuracy, providing more reliable cardiovascular health services.

Comfort and reliability

Ensuring a comfortable wearing experience is crucial for the practical application of wearable devices. Future devices need lightweight designs that provide adequate ventilation and comfort at the skin contact areas. Usability is equally important; devices should be operable by even non-professionals. Future models will feature user-friendly interfaces with large screens, voice interaction, tactile feedback, and streamlined user processes, making it easy for users to access and understand their cardiovascular health data effortlessly.

The stability of the system is essential for the accuracy and reliability of wearable devices, especially in long-term monitoring. As wearable technology evolves, enhanced sensors and algorithms will improve the quality of biological signal acquisition and analysis. This advancement will enable effective monitoring of critical health indicators such as heart function, BP, and heart rate variability, providing more dependable health data. Improved stability will also allow medical professionals to better track patient cardiovascular status, facilitating accurate diagnoses and treatment planning.

Reducing the impact on users is a pivotal direction for the development of smart wearable devices. Long-term wear should minimally affect user comfort and freedom. To reduce user impact, future devices will aim to avoid excessive diagnostic procedures. For instance, studies like the apple heart research have shown that overdiagnosis of atrial fibrillation can increase the burden on clinics and elevate patient stress [189]. Future wearable devices will focus on seamless integration into a broader health ecosystem. Integration with health management tools and electronic medical records systems allows for unified data management and more precise diagnostics.

Safety

Data security is crucial when using wearable devices for cardiovascular health monitoring[190,191]. The primary design focus of smart wearable programs should be the protection of user data privacy. Since device manufacturers often collect data, robust security mechanisms are essential in future devices to safeguard personal and medical information against unauthorized access and use. Enhancements in key management, encryption, and secure data transmission protocols will be central to device development to maintain data privacy and integrity.

Mechanical safety is vital for user safety during long-term use of wearable devices. Electrical risks like short circuits and overheating, mechanical risks such as breakage and wear, and biological risks including biocompatibility and infection must be carefully managed.

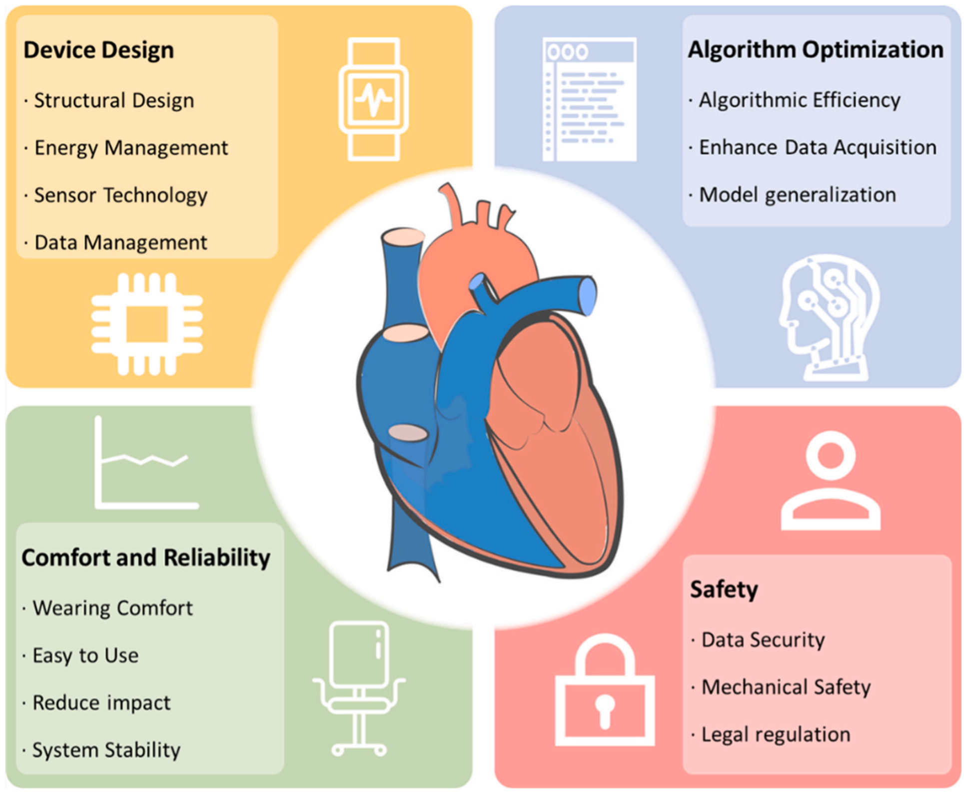

Fig. 17. Outlook of intelligent wearable devices for cardiovascular health monitoring.

Developing strategies to handle mechanical stress, prevent electrical failures, and enhance device integration is crucial. Future devices must meet safety standards to prevent skin irritation, allergies, and other potential damages. Additionally, the fit and stability of the device are crucial to ensure a safe and comfortable user experience. Effective regulation is essential for the safe operation of wearable devices. Before deployment, stringent testing procedures and regulatory standards must be established by relevant authorities to ensure device safety and effectiveness.

Author statement

We have confirmed that the our manuscript has not been published previously (except in the form of an abstract, a published lecture or academic thesis), that it is not under consideration for publication elsewhere, that its publication is approved by all authors and tacitly or explicitly by the responsible authorities where the work was carried out, and that, if accepted, it will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright-holder.

CRediT authorship contribution statement

Yiqian Wang: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Zhou Li:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Yang Zou:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used OpenAI in order to improve and edit some of sentences. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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The table of contents entry

This work summarizes key indicators of cardiovascular health and describes diversified cardiovascular health monitoring sensing technologies. It highlights advancements in wearable sensing technologies integrated with AI, showcasing application cases. The challenges in AI integration into wearable devices are also discussed. This integration promises to enhance diagnostics and screening for cardiovascular diseases.

Data Availability

No data was used for the research described in the article.

References

[1] J.I. Davies, S.K. Reddiar, L.R. Hirschhorn, C. Ebert, M.-E. Marcus, J.A. Seiglie, Z. Zhumadilov, A. Supiyev, L. Sturua, B.K. Silver, A.M. Sibai, S. Quesnel-Crooks, B. Norov, J.K. Mwangi, O.M. Omar, R. Wong-McClure, M.T. Mayige, J.S. Martins, N. Lunet, D. Labadarios, K.B. Karki, G.B. Kagaruki, J.M.A. Jorgensen, N. C. Hwalla, D. Houinato, C. Houehanou, D. Guwatudde, M.S. Gurung, P. Bovet, B. W. Bicaba, K.K. Aryal, M. Msaidie, G. Andall-Brereton, G. Brian, A. Stokes, S. Vollmer, T. Barnighausen, R. Atun, P. Geldsetzer, J. Manne-Goehler, L. M. Jaacks, Association between country preparedness indicators and quality clinical care for cardiovascular disease risk factors in 44 lower- and middle-income countries: a multicountry analysis of survey data, PLos Med 17 (2020) e1003268, https://doi.org/10.1371/journal.pmed.1003268.

[2] A. Timmis, N. Townsend, C. Gale, R. Grobbee, N. Maniadakis, M. Flather, E. Wilkins, L. Wright, R. Vos, J. Bax, M. Blum, F. Pinto, P. Vardas, ESC Scientific Document Group, A. Goda, A.F. Demiraj, F. Weidinger, B. Metzler, F. Ibrahimov, A.A. Pasquet, M. Claeys, Y. Thorton, Z. Kusljugic, E. Smajic, V. Velchev, N. Ivanov, L. Antoniades, P. Agathangelou, M. Táborský, C. Gerdes, M. Viigima, P.M. Juhani, Y. Juilliere, S. Cattan, A. Aladashvili, C. Hamm, K.-H. Kuck, K. Papoutsis, K. Bestehorn, S. Foussas, G. Giannoulidou, C. Varounis, I. Kallikazaros, R.G. Kiss, T. Czétényi, D. Becker, T. Gudnason, P. Kearney, K. McDonald, Y. Rozenman, B. Ziv, L. Bolognese, P. Luciolli, G. Boriani, S. Berkinbayev, A. Rakisheva, E. Mirrakhimov, A. Erglis, S. Jegere, G. Marinskis, J. Beissel, N. Marchal, S. Kedev, R.G. Xuereb, T. Tilney, T. Felice, M. Popovici, J. Bax, B. Mulder, M. Simoons, M. Elsendoorn, T.K. Steigen, D. Atar, Z. Kalarus, M. Tendera, J.S. Cardoso, J. Ribeiro, C. Mateus, G. Tatu-Chitoiu, P. Seferovic, B. Beleslin, I. Simkova, P. Durcikova, V. Belicova, Z. Fras, S. Radelj, J.R. Gonzalez Juanatey, S. Legendre, F. Braunschweig, U.P. Kaufmann, M. Rudiger-Sturchler, L. Tokgozoglu, A. Unver, V. Kovalenko, E. Nesukay, A. Naum, P.T. De Courtelary, S. Martin, D. Sebastiao, D. Ghislain, I. Bardinet, S. Logstrup, European Society of Cardiology: Cardiovascular Disease Statistics 2017, Eur. Heart J. 39 (2018) 508–579, https://doi.org/10.1093/eurheartj/ehx628.

[3] E.J. Benjamin, P. Muntner, A. Alonso, M.S. Bittencourt, C.W. Callaway, A. P. Carson, A.M. Chamberlain, A.R. Chang, S. Cheng, S.R. Das, F.N. Delling, L. Djousse, M.S.V. Elkind, J.F. Ferguson, M. Fornage, L.C. Jordan, S.S. Khan, B. M. Kissela, K.L. Knutson, T.W. Kwan, D.T. Lackland, T.T. Lewis, J.H. Lichtman, C. T. Longenecker, M.S. Loop, P.L. Lutsey, S.S. Martin, K. Matsushita, A.E. Moran, M.E. Mussolino, M. O'Flaherty, A. Pandey, A.M. Perak, W.D. Rosamond, G. A. Roth, U.K.A. Sampson, G.M. Satou, E.B. Schroeder, S.H. Shah, N.L. Spartano, A. Stokes, D.L. Tirschwell, C.W. Tsao, M.P. Turakhia, L.B. VanWagner, J. T. Wilkins, S.S. Wong, S.S. Virani, On behalf of the American Heart Association Council on epidemiology and prevention statistics committee and stroke statistics subcommittee, heart disease and stroke statistics—2019 update: a report From the American Heart Association, Circulation 139 (2019), https://doi.org/10.1161/CIR.0000000000000659.

[4] A. Timmis, N. Townsend, C.P. Gale, A. Torbica, M. Lettino, S.E. Petersen, E. A. Mossialos, A.P. Maggioni, D. Kazakiewicz, H.T. May, D. De Smedt, M. Flather, L. Zuhlke, J.F. Beltrame, R. Huculeci, L. Tavazzi, G. Hindricks, J. Bax, B. Casadei, S. Achenbach, L. Wright, P. Vardas, European Society of Cardiology, L. Mimoza, G. Artan, D. Aurel, M. Chettibi, N. Hammoudi, H. Sisakian, S. Pepoyan, B. Metzler, P. Siostrzonek, F. Weidinger, T. Jahangirov, F. Aliyev, Y. Rustamova, N. Manak, A. Mrochak, P. Lancellotti, A. Pasquet, M. Claeys, Z. Kušljugić, L. Dizdarević Hudić, E. Smajić, M.P. Tokmakova, P.M. Gatzov, D. Milicic, M. Bergovec, C. Christou, H.H. Moustra, T. Christodoulides, A. Linhart, M. Taborsky, H.S. Hansen, L. Holmvang, S.D. Kristensen, M. Abdelhamid, K. Shokry, P. Kampus, M. Viigimaa, E. Ryödi, M. Niemelä, T.T. Rissanen, J.-Y. Le Heuzey, M. Gilard, A. Aladashvili, A. Gamkrelidze, M. Kereselidze, A. Zeiher, H. Katus, K. Bestehorn, C. Tsioufis, J. Goudevenos, Z. Csanádi, D. Becker, K. Tóth, Þ Jóna Hrafnkelsdóttir, J. Crowley, P. Kearney, B. Dalton, D. Zahger, A. Wolak, D. Gabrielli, C. Indolfi, S. Urbinati, G. Imantayeva, S. Berkinbayev, G. Bajraktari, A. Ahmeti, G. Berisha, M. Erkin, A. Saamay, A. Erglis, I. Bajare, S. Jegere, M. Mohammed, A. Sarkis, G. Saadeh, R. Zvirblyte, G. Sakalyte, R. Slapikas, K. Ellafi, F. El Ghamari, C. Banu, J. Beissel, T. Felice, S.C. Buttigieg, R.G. Xuereb, M. Popovici, A. Boskovic, M. Rabrenovic, S. Ztot, S. Abir-Khalil, A.C. Van Rossum, B.J.M. Mulder, M.W. Elsendoorn, E. Srbinovska-Kostovska, J. Kostov, B. Marjan, T. Steigen, O.C. Mjølstad, P. Ponikowski, A. Witkowski, P. Jankowski, V.M. Gil, J. Mimoso, S. Baptista, D. Vinereanu, O. Chioncel, B.A. Popescu, E. Shlyakhto, R. Oganov, M. Foscoli, M. Zavatta, A.D. Dikic, B. Beleslin, M.R. Radovanovic, P. Hlivák, R. Hatala, G. Kaliská, M. Kenda, Z. Fras, M. Anguita, Á. Cequier, J. Muñiz, S. James, B. Johansson, P. Platonov, M.J. Zellweger, G.B. Pedrazzini, D. Carballo, H.E. Shebli, S. Kabbani, L. Abid, F. Addad, E. Bozkurt, M. Kayıkçıoğlu, M.K. Erol, V. Kovalenko, E. Nesukay, A. Wragg, P. Ludman, S. Ray, R. Kurbanov, D. Boateng, G. Daval, V. De Benito Rubio, D. Sebastiao, P. T. De Courtelary, I. Bardinet, European Society of cardiology: cardiovascular disease statistics 2019, Eur. Heart J. 41 (2020) 12–85, https://doi.org/10.1093/eurheartj/ehz859.

[5] R.A. Carels, L.A. Darby, H.M. Cacciapaglia, O.M. Douglass, Reducing cardiovascular risk factors in postmenopausal women through a lifestyle change intervention, J. Women'S. Health 13 (2004) 412–426, https://doi.org/10.1089/154099904323087105.

[6] C.K. Chow, K.K. Teo, S. Rangarajan, S. Islam, R. Gupta, A. Avezum, A. Bahonar, J. Chifamba, G. Dagenais, R. Diaz, K. Kazmi, F. Lanas, L. Wei, P. Lopez-Jaramillo, L. Fanghong, N.H. Ismail, T. Puoane, A. Rosengren, A. Szuba, A. Temizhan, A. Wielgosz, R. Yusuf, A. Yusufali, M. McKee, L. Liu, P. Mony, S. Yusuf, PURE (Prospective urban rural epidemiology) study investigators, prevalence, awareness, treatment, and control of hypertension in rural and urban communities in high-, middle-, and low-income countries, JAMA 310 (2013) 959–968, https://doi.org/10.1001/jama.2013.184182.

[7] T. Zhang, N. Liu, J. Xu, Z. Liu, Y. Zhou, Y. Yang, S. Li, Y. Huang, S. Jiang, Flexible electronics for cardiovascular healthcare monitoring, Innovation 4 (2023) 100485, https://doi.org/10.1016/j.xinn.2023.100485.

[8] M.M. Baig, H. Gholamhosseini, M.J. Connolly, A comprehensive survey of wearable and wireless ECG monitoring systems for older adults, Med Biol. Eng. Comput. 51 (2013) 485–495, https://doi.org/10.1007/s11517-012-1021-6.

[9] S. Rastegar, H. GholamHosseini, A. Lowe, Non-invasive continuous blood pressure monitoring systems: current and proposed technology issues and challenges, Phys. Eng. Sci. Med 43 (2020) 11–28, https://doi.org/10.1007/s13246-019-00813-x.

[10] W. Wu, L. Wang, G. Shen, Flexible photoplethysmographic sensing devices for intelligent medical treatment, J. Mater. Chem. C. 11 (2022) 97–112, https://doi.org/10.1039/D2TC03318F.

[11] M.J. Tadi, E. Lehtonen, T. Koivisto, M. Pankaala, A. Paasio, M. Teras, Seismocardiography: Toward Heart Rate Variability (HRV) Estimation, in: Ieee International Symposium on Medical Measurements and Applications (Memea) Proceedings, 2015, Ieee, New York, 2015, pp. 261–266, https://www.webofscience.com/wos/alldb/full-record/WOS:000380610600049 (accessed February 21, 2023).

[12] J. Ji, M. Dong, Q. Lin, K.C. Tan, Noninvasive Cuffless Blood Pressure Estimation With Dendritic Neural Regression, IEEE T. Cybern. (n.d.). https://doi.org/10.1109/TCYB.2022.3141380.

[13] D.G. Shin, M.-K. Kang, Y.B. Seo, J. Choi, S.Y. Choi, S. Choi, J.R. Cho, N. Lee, Factors associated with abnormal left ventricular ejection fraction (decreased or increased) in patients with sepsis in the intensive care unit, PLoS One 15 (2020) e0229563, https://doi.org/10.1371/journal.pone.0229563.

[14] A. Argha, B.G. Celler, N.H. Lovell, Artificial intelligence based blood pressure estimation from auscultatory and oscillometric waveforms: a methodological review, IEEE Rev. Biomed. Eng. 15 (2022) 152–168, https://doi.org/10.1109/RBME.2020.3040715.

[15] S. Gupta, A. Singh, A. Sharma, Dynamic Large Artery Stiffness Index for Cuffless Blood Pressure Estimation, IEEE Sens. Lett. 6 (2022) 1–4, https://doi.org/10.1109/LSENS.2022.3157060.

[16] J. Yang, G. Zhang, Q. Shang, M. Wu, L. Huang, H. Jiang, Detecting hemodynamic changes in the foot vessels of diabetic patients by photoacoustic tomography, J. Biophotonics 13 (2020) e202000011, https://doi.org/10.1002/jbio.202000011.

[17] S. Qiu, B.P.Y. Yan, N. Zhao, Stroke-volume-allocation model enabling wearable sensors for vascular age and cardiovascular disease assessment, Npj Flex. Electron 8 (2024) 1–10, https://doi.org/10.1038/s41528-024-00307-1.

[18] K. Bayoumy, M. Gaber, A. Elshafeey, O. Mhaimeed, E.H. Dineen, F.A. Marvel, S. S. Martin, E.D. Muse, M.P. Turakhia, K.G. Tarakji, M.B. Elshazly, Smart wearable devices in cardiovascular care: where we are and how to move forward, Nat. Rev. Cardiol. 18 (2021) 581–599, https://doi.org/10.1038/s41569-021-00522-7.

[19] K.B. Kim, H.J. Baek, Photoplethysmography in wearable devices: a comprehensive review of technological advances, current challenges, and future directions, Electronics 12 (2023) 2923, https://doi.org/10.3390/electronics12132923.

[20] C. Qin, Y. Li, C. Liu, X. Ma, Cuff-less blood pressure prediction based on photoplethysmography and modified ResNet, Bioengeering 10 (2023) 400, https://doi.org/10.3390/bioengineering10040400.

[21] S.N. Ahmed, P. Prakasam, A systematic review on intracranial aneurysm and hemorrhage detection using machine learning and deep learning techniques, Prog. Biophys. Mol. Biol. 183 (2023) 1–16, https://doi.org/10.1016/j.pbiomolbio.2023.07.001.

[22] M. Lown, M. Brown, C. Brown, A.M. Yue, B.N. Shah, S.J. Corbett, G. Lewith, B. Stuart, M. Moore, P. Little, Machine learning detection of atrial fibrillation using wearable technology, PLOS ONE 15 (2020) e0227401, https://doi.org/10.1371/journal.pone.0227401.

[23] R. Czabanski, K. Horoba, J. Wrobel, A. Matonia, R. Martinek, T. Kupka, M. Jezewski, R. Kahankova, J. Jezewski, J.M. Leski, Detection of atrial fibrillation episodes in long-term heart rhythm signals using a support vector machine, Sensors 20 (2020) 765, https://doi.org/10.3390/s20030765.

[24] C. Guang-Yi, G. Li-Sha, L. Yue-Chun, Role of heart rate reduction in the management of myocarditis, Curr. Pharm. Des. 24 (2018) 365–378, https://doi.org/10.2174/1381612824666180111105923.

[25] S. Sahoo, M. Dash, S. Behera, S. Sabut, Machine learning approach to detect cardiac arrhythmias in ECG Signals: a survey, IRBM 41 (2020) 185–194, https://doi.org/10.1016/j.irbm.2019.12.001.

[26] P.A. Noseworthy, Z.I. Attia, E.M. Behnken, R.E. Giblon, K.A. Bews, S. Liu, T. A. Gosse, Z.D. Linn, Y. Deng, J. Yin, B.J. Gersh, J. Graff-Radford, A.A. Rabinstein, K.C. Siontis, P.A. Friedman, X. Yao, Artificial intelligence-guided screening for atrial fibrillation using electrocardiogram during sinus rhythm: a prospective non-randomised interventional trial, Lancet 400 (2022) 1206–1212, https://doi.org/10.1016/S0140-6736(22)01637-3.

[27] I. Matias, N. Garcia, S. Pirbhulal, V. Felizardo, N. Pombo, H. Zacarias, M. Sousa, E. Zdravevski, Prediction of atrial fibrillation using artificial intelligence on electrocardiograms: a systematic review, Comput. Sci. Rev. 39 (2021) 100334, https://doi.org/10.1016/j.cosrev.2020.100334.

[28] A. de Leon, V. Neira, N. Alhammad, W. Hopman, S. Hansom, S. Chacko, C. Simpson, D. Redfearn, H. Abdollah, A. Arauz, A. Baranchuk, A. Enriquez, Electrocardiographic predictors of atrial fibrillation in patients with cryptogenic stroke, Pacing Clin. Electrophysiol. 45 (2022) 176–181, https://doi.org/10.1111/pace.14418.

[29] V. Jahmunah, E.Y.K. Ng, R.-S. Tan, S.L. Oh, U.R. Acharya, Explainable detection of myocardial infarction using deep learning models with Grad-CAM technique on ECG signals, Comput. Biol. Med. 146 (2022) 105550, https://doi.org/10.1016/j.compbiomed.2022.105550.
[30] A. Barandiarán Aizpurua, S. Sanders-van Wijk, H.-P. Brunner-La Rocca, M. Henkens, S. Heymans, L. Beussink-Nelson, S.J. Shah, V.P.M. van Empel, Validation of the HFA-PEFF score for the diagnosis of heart failure with preserved ejection fraction, Eur. J. Heart Fail. 22 (2020) 413–421, https://doi.org/10.1002/ejhf.1614.
[31] Y.N.V. Reddy, D.M. Kaye, M.L. Handoko, A.A. van de Bovenkamp, R.J. Tedford, C. Keck, M.J. Andersen, K. Sharma, R.K. Trivedi, R.E. Carter, M. Obokata, F. H. Verbrugge, M.M. Redfield, B.A. Borlaug, Diagnosis of heart failure with preserved ejection fraction among patients with unexplained dyspnea, JAMA Cardiol. 7 (2022) 891–899, https://doi.org/10.1001/jamacardio.2022.1916.
[32] F.D. Fuchs, P.K. Whelton, High blood pressure and cardiovascular disease, Hypertension 75 (2020) 285–292, https://doi.org/10.1161/HYPERTENSIONAHA.119.14240.
[33] K. Meng, J. Chen, X. Li, Y. Wu, W. Fan, Z. Zhou, Q. He, X. Wang, X. Fan, Y. Zhang, J. Yang, Z.L. Wang, Flexible weaving constructed self-powered pressure sensor enabling continuous diagnosis of cardiovascular disease and measurement of cuffless blood pressure, Adv. Funct. Mater. 29 (2019) 1806388, https://doi.org/10.1002/adfm.201806388.
[34] K. Venugopal, P. Panchatcharam, A. Chandrasekhar, V. Shanmugasundaram, Comprehensive review on triboelectric nanogenerator based wrist pulse measurement: sensor fabrication and diagnosis of arterial pressure, ACS Sens 6 (2021) 1681–1694, https://doi.org/10.1021/acssensors.0c02324.
[35] G. Ma, J. Zhang, J. Liu, L. Wang, Y. Yu, A Multi-parameter fusion method for cuffless continuous blood pressure estimation based on electrocardiogram and photoplethysmogram, Micromachines 14 (2023) 804, https://doi.org/10.3390/mi14040804.
[36] K. Meng, X. Xiao, W. Wei, G. Chen, A. Nashalian, S. Shen, X. Xiao, J. Chen, Wearable pressure sensors for pulse wave monitoring, Adv. Mater. 34 (2022) 2109357, https://doi.org/10.1002/adma.202109357.
[37] Z. Alizadeh Sani, A. Shalbaf, H. Behnam, R. Shalbaf, Automatic computation of left ventricular volume changes over a cardiac cycle from echocardiography images by nonlinear dimensionality reduction, J. Digit Imaging 28 (2015) 91–98, https://doi.org/10.1007/s10278-014-9722-z.
[38] F.N. van de Vosse, N. Stergiopulos, Pulse wave propagation in the arterial tree, Annu. Rev. Fluid Mech. 43 (2011) 467–499, https://doi.org/10.1146/annurev-fluid-122109-160730.
[39] I.B. Wilkinson, J.R. Cockcroft, D.J. Webb, Pulse wave analysis and arterial stiffness, J. Cardiovasc Pharm. 32 (3) (1998).
[40] L. Stoner, J.M. Young, S. Fryer, Assessments of Arterial Stiffness and Endothelial Function Using Pulse Wave Analysis, Int J. Vasc. Med 2012 (2012) 903107, https://doi.org/10.1155/2012/903107.
[41] A.P. Avolio, M. Butlin, A. Walsh, Arterial blood pressure measurement and pulse wave analysis—their role in enhancing cardiovascular assessment, Physiol. Meas. 31 (2009) R1, https://doi.org/10.1088/0967-3334/31/1/R01.
[42] L. Wang, H. Wang, Mechanics modeling and inverse analyses of pulse wave system from the view-point of traditional chinese medicine, Am. Soc. Mech. Eng. Digit. Collect. (2016), https://doi.org/10.1115/OMAE2016-55106.
[43] Z. Yi, Z. Liu, W. Li, T. Ruan, X. Chen, J. Liu, B. Yang, W. Zhang, Piezoelectric Dynamics of Arterial Pulse for Wearable Continuous Blood Pressure Monitoring, Adv. Mater. 34 (2022) 2110291, https://doi.org/10.1002/adma.202110291.
[44] E. Chen, J. Jiang, R. Su, M. Gao, S. Zhu, J. Zhou, Y. Huo, A new smart wristband equipped with an artificial intelligence algorithm to detect atrial fibrillation, Heart Rhythm 17 (2020) 847–853, https://doi.org/10.1016/j.hrthm.2020.01.034.
[45] T. Pereira, N. Tran, K. Gadhoumi, M.M. Pelter, D.H. Do, R.J. Lee, R. Colorado, K. Meisel, X. Hu, Photoplethysmography based atrial fibrillation detection: a review, Npj Digit. Med. 3 (2020) 1–12, https://doi.org/10.1038/s41746-019-0207-9.
[46] M. Nitzan, A. Romem, R. Koppel, Pulse oximetry: fundamentals and technology update, Med Devices-Evid. Res 7 (2014) 231–239, https://doi.org/10.2147/MDER.S47319.
[47] G.J. Williams, A. Al-Baraikan, F.E. Rademakers, F. Ciravegna, F.N. van de Vosse, A. Lawrie, A. Rothman, E.A. Ashley, M.R. Wilkins, P.V. Lawford, S.W. Omholt, U. Wisløff, D.R. Hose, T.J.A. Chico, J.P. Gunn, P.D. Morris, Wearable technology and the cardiovascular system: the future of patient assessment, Lancet Digit. Health 5 (2023) e467–e476, https://doi.org/10.1016/S2589-7500(23)00087-0.
[48] L. Dagher, H. Shi, Y. Zhao, N.F. Marrouche, Wearables in cardiology: here to stay, Heart Rhythm 17 (2020) 889–895, https://doi.org/10.1016/j.hrthm.2020.02.023.
[49] E.O. Polat, G. Mercier, I. Nikitskiy, E. Puma, T. Galan, S. Gupta, M. Montagut, J. J. Piqueras, M. Bouwens, T. Durduran, G. Konstantatos, S. Goossens, F. Koppens, Flexible graphene photodetectors for wearable fitness monitoring, Sci. Adv. 5 (2019) eaaw7846, https://doi.org/10.1126/sciadv.aaw7846.
[50] T. Yokota, P. Zalar, M. Kaltenbrunner, H. Jinno, N. Matsuhisa, H. Kitanosako, Y. Tachibana, W. Yukita, M. Koizumi, T. Someya, Ultraflexible organic photonic skin, Sci. Adv. 2 (2016) e1501856, https://doi.org/10.1126/sciadv.1501856.
[51] J.L. Moraes, M.X. Rocha, G.G. Vasconcelos, J.E. Vasconcelos Filho, V.H.C. De Albuquerque, A.R. Alexandria, Advances in photopletysmography signal analysis for biomedical applications, Sensors 18 (2018) 1894, https://doi.org/10.3390/s18061894.
[52] X.-L. Yang, G.-Z. Liu, Y.-H. Tong, H. Yan, Z. Xu, Q. Chen, X. Liu, H.-H. Zhang, H.-B. Wang, S.-H. Tan, The history, hotspots, and trends of electrocardiogram, J. Geriatr. Cardiol. 12 (2015) 448–456, https://doi.org/10.11909/j.issn.1671-5411.2015.04.018.
[53] J. Lin, R. Fu, X. Zhong, P. Yu, G. Tan, W. Li, H. Zhang, Y. Li, L. Zhou, C. Ning, Wearable sensors and devices for real-time cardiovascular disease monitoring, Cell Rep. Phys. Sci. 2 (2021) 100541, https://doi.org/10.1016/j.xcrp.2021.100541.
[54] A. Abdou, S. Krishnan, Horizons in Single-Lead ECG Analysis From Devices to Data, Front. Signal Process. 2 (2022), https://doi.org/10.3389/frsip.2022.866047.
[55] G. Hindricks, T. Potpara, N. Dagres, E. Arbelo, J.J. Bax, C. Blomström-Lundqvist, G. Boriani, M. Castella, G.-A. Dan, P.E. Dilaveris, L. Fauchier, G. Filippatos, J. M. Kalman, M. La Meir, D.A. Lane, J.-P. Lebeau, M. Lettino, G.Y.H. Lip, F.J. Pinto, G.N. Thomas, M. Valgimigli, I.C. Van Gelder, B.P. Van Putte, C.L. Watkins, ESC Scientific Document Group, 2020 ESC Guidelines for the diagnosis and management of atrial fibrillation developed in collaboration with the European Association for Cardio-Thoracic Surgery (EACTS): The Task Force for the diagnosis and management of atrial fibrillation of the European Society of Cardiology (ESC) Developed with the special contribution of the European Heart Rhythm Association (EHRA) of the ESC, Eur. Heart J. 42 (2021) 373–498, https://doi.org/10.1093/eurheartj/ehaa612.
[56] T.S. Hartikainen, N.A. Sörensen, P.M. Haller, A. Goßling, J. Lehmacher, T. Zeller, S. Blankenberg, D. Westermann, J.T. Neumann, Clinical application of the 4th Universal Definition of Myocardial Infarction, Eur. Heart J. 41 (2020) 2209–2216, https://doi.org/10.1093/eurheartj/ehaa035.
[57] Gara Patrick T. O, F.G. Kushner, D.D. Ascheim, D.E. Casey, M.K. Chung, L.J.A. de, S.M. Ettinger, J.C. Fang, F.M. Fesmire, B.A. Franklin, C.B. Granger, H. M. Krumholz, J.A. Linderbaum, D.A. Morrow, L.K. Newby, J.P. Ornato, N. Ou, M. J. Radford, -Holland Jacqueline E. Tamis, C.L. Tommaso, C.M. Tracy, Y.J. Woo, D. X. Zhao, ACCF/AHA guideline for the management of ST-elevation myocardial infarction, J. Am. Coll. Cardiol. 61 (2013) (2013) e78–e140, https://doi.org/10.1016/j.jacc.2012.11.019.
[58] S.S. Al-Zaiti, J.A. Fallavollita, Y.-W.B. Wu, M.R. Tomita, M.G. Carey, Electrocardiogram-based predictors of clinical outcomes: A meta-analysis of the prognostic value of ventricular repolarization, Heart Lung 43 (2014) 516–526, https://doi.org/10.1016/j.hrtlng.2014.05.004.
[59] B. Maisch, H. Mahrholdt, ESC-Leitlinie 2014 zur Diagnose und zum Management der hypertrophischen Kardiomyopathie, Herz 39 (2014) 919–930, https://doi.org/10.1007/s00059-014-4177-z.
[60] E. Vavrinsky, J. Subjak, M. Donoval, A. Wagner, T. Zavodnik, H. Svobodova, Application of modern multi-sensor holter in diagnosis and treatment, Sensors 20 (2020) 2663, https://doi.org/10.3390/s20092663.
[61] H.L. Kennedy, The History, science, and innovation of holter technology, Ann. Noninvasive Electrocardiol. 11 (2006) 85–94, https://doi.org/10.1111/j.1542-474X.2006.00067.x.
[62] S. Singhal, M. Kumar, A systematic review on artificial intelligence-based techniques for diagnosis of cardiovascular arrhythmia diseases: challenges and opportunities, Arch. Comput. Methods Eng. (2022), https://doi.org/10.1007/s11831-022-09823-7.
[63] T. Cui, Y. Qiao, D. Li, X. Huang, L. Yang, A. Yan, Z. Chen, J. Xu, X. Tan, J. Jian, Z. Li, S. Ji, H. Liu, Y. Yang, X. Zhang, T.-L. Ren, Multifunctional, breathable MXene-PU mesh electronic skin for wearable intelligent 12-lead ECG monitoring system, Chem. Eng. J. 455 (2023) 140690, https://doi.org/10.1016/j.cej.2022.140690.
[64] K. Huang, J. Liu, S. Lin, Y. Wu, E. Chen, Z. He, M. Lei, Flexible silver nanowire dry electrodes for long-term electrocardiographic monitoring, Adv. Compos. Hybrid. Mater. 5 (2022) 220–228, https://doi.org/10.1007/s42114-021-00322-0.
[65] K.C. Siontis, P.A. Noseworthy, Z.I. Attia, P.A. Friedman, Artificial intelligence-enhanced electrocardiography in cardiovascular disease management, Nat. Rev. Cardiol. 18 (2021) 465–478, https://doi.org/10.1038/s41569-020-00503-2.
[66] V. Sangha, B.J. Mortazavi, A.D. Haimovich, A.H. Ribeiro, C.A. Brandt, D. L. Jacoby, W.L. Schulz, H.M. Krumholz, A.L.P. Ribeiro, R. Khera, Automated multilabel diagnosis on electrocardiographic images and signals, Nat. Commun. 13 (2022) 1583, https://doi.org/10.1038/s41467-022-29153-3.
[67] S. Gong, L.W. Yap, Y. Zhang, J. He, J. Yin, F. Marzbanrad, D.M. Kaye, W. Cheng, A gold nanowire-integrated soft wearable system for dynamic continuous non-invasive cardiac monitoring, Biosens. Bioelectron. 205 (2022) 114072, https://doi.org/10.1016/j.bios.2022.114072.
[68] M. Amini, J. Hisdal, H. Kalvøy, Applications of bioimpedance measurement techniques in tissue engineering, J. Electr. Bioimpedance 9 (2018) 142–158, https://doi.org/10.2478/joeb-2018-0019.
[69] G. Anand, Y. Yu, A. Lowe, A. Kalra, Bioimpedance analysis as a tool for hemodynamic monitoring: overview, methods and challenges, Physiol. Meas. 42 (2021) 03TR01, https://doi.org/10.1088/1361-6579/abe80e.
[70] D. Naranjo-Hernández, J. Reina-Tosina, M. Min, Fundamentals, recent advances, and future challenges in bioimpedance devices for healthcare applications, J. Sens. 2019 (2019) e9210258, https://doi.org/10.1155/2019/9210258.
[71] O. Byambasukh, M.F. Eisenga, R.T. Gansevoort, S.J. Bakker, E. Corpeleijn, Body fat estimates from bioelectrical impedance equations in cardiovascular risk assessment: The PREVEND cohort study, Eur. J. Prev. Cardiol. 26 (2019) 905–916, https://doi.org/10.1177/2047487319833283.
[72] T.K. Bera, Bioelectrical impedance methods for noninvasive health monitoring: a review, J. Med. Eng. 2014 (2014) 1–28, https://doi.org/10.1155/2014/381251.
[73] M.A. Khaled, M. Khatun, M. Haque, I. Kabir, D. Mahalanabis, Single, dual and multi-frequency bioimpedance to measure human body composition. Proceedings of the First Regional Conference, IEEE Engineering in Medicine and Biology Society and 14th Conference of the Biomedical Engineering Society of India, An

International Meet, 1995, pp. 1/87–1/88, https://doi.org/10.1109/RCEMBS.1995.508703.
[74] P. Kassanos, Bioimpedance sensors: a tutorial, IEEE Sens. J. 21 (2021) 22190–22219, https://doi.org/10.1109/JSEN.2021.3110283.
[75] A.V. Sahakian, W.J. Tompkins, J.G. Webster, Electrode motion artifacts in electrical impedance pneumography, IEEE Trans. Biomed. Eng. BME 32 (1985) 448–451, https://doi.org/10.1109/TBME.1985.325453.
[76] M. Etemadi, O.T. Inan, Wearable ballistocardiogram and seismocardiogram systems for health and performance, J. Appl. Physiol. 124 (2018) 452–461, https://doi.org/10.1152/japplphysiol.00298.2017.
[77] D. Rai, H.K. Thakkar, S.S. Rajput, J. Santamaria, C. Bhatt, F. Roca, A comprehensive review on seismocardiogram: current advancements on acquisition, annotation, and applications, Mathematics 9 (2021) 2243, https://doi.org/10.3390/math9182243.
[78] X. Han, X. Wu, J. Wang, H. Li, K. Cao, H. Cao, K. Zhong, X. Yang, The Latest progress and development trend in the research of ballistocardiography (BCG) and seismocardiogram (scg) in the field of health care, Appl. Sci. 11 (2021) 8896, https://doi.org/10.3390/app11198896.
[79] P. Mounsey, Præcordial ballistocardiography, Br, Heart J. 19 (1957) 259–271.
[80] I. Starr, A.J. Rawson, H.A. Schroeder, N.R. Joseph, Studies on the estimation of cardiac ouptut in man, and of abnormalities in cardiac function, from the heart's recoil and the blood's impacts; the ballistocardiogram, Am. J. Physiol. -Leg. Content 127 (1939) 1–28, https://doi.org/10.1152/ajplegacy.1939.127.1.1.
[81] C.-S. Kim, S.L. Ober, M.S. McMurtry, B.A. Finegan, O.T. Inan, R. Mukkamala, J.-O. Hahn, Ballistocardiogram: Mechanism and Potential for Unobtrusive Cardiovascular Health Monitoring, Sci. Rep. 6 (2016) 31297, https://doi.org/10.1038/srep31297.
[82] J.M. Zanetti, K. Tavakolian, Seismocardiography: Past, present and future, 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC) 2013 (2013) 7004–7007, https://doi.org/10.1109/EMBC.2013.6611170.
[83] I. Sadek, J. Biswas, B. Abdulrazak, Ballistocardiogram signal processing: a review, Health Inf. Sci. Syst. 7 (2019) 10, https://doi.org/10.1007/s13755-019-0071-7.
[84] X. Wen, Y. Huang, X. Wu, B. Zhang, A Feasible Feature Extraction Method for Atrial Fibrillation Detection From BCG, IEEE J. Biomed. Health Inform. 24 (2020) 1093–1103, https://doi.org/10.1109/JBHI.2019.2927165.
[85] O.T. Inan, P.-F. Migeotte, K.-S. Park, M. Etemadi, K. Tavakolian, R. Casanella, J. Zanetti, J. Tank, I. Funtova, G.K. Prisk, M. Di Rienzo, Ballistocardiography and seismocardiography: a review of recent advances, IEEE J. Biomed. Health Inform. 19 (2015) 1414–1427, https://doi.org/10.1109/JBHI.2014.2361732.
[86] M.J.S. Lowe, D.N. Alleyne, P. Cawley, Defect detection in pipes using guided waves, Ultrasonics 36 (1998) 147–154, https://doi.org/10.1016/S0041-624X(97)00038-3.
[87] B.W. Drinkwater, P.D. Wilcox, Ultrasonic arrays for non-destructive evaluation: A review, NDT E Int. 39 (2006) 525–541, https://doi.org/10.1016/j.ndteint.2006.03.006.
[88] N. Waingankar, B.R. Gilbert, History of Ultrasound in Urology, in: P.F. Fulgham, B.R. Gilbert (Eds.), Practical Urological Ultrasound, Springer, New York, NY, 2013, pp. 1–8, https://doi.org/10.1007/978-1-59745-351-6_1.
[89] N.C. Nanda, M.C. Hsiung, J.P. Youngblood, D. Maulik, Doppler color flow mapping of the fetal heart, Angiology 37 (1986) 628–632, https://doi.org/10.1177/000331978603700902.
[90] U.M. Hamper, M.R. DeJong, C.I. Caskey, S. Sheth, Power Doppler imaging: clinical experience and correlation with color Doppler US and other imaging modalities, RadioGraphics 17 (1997) 499–513, https://doi.org/10.1148/radiographics.17.2.9084086.
[91] S. Yagel, S.M. Cohen, I. Shapiro, D.V. Valsky, 3D and 4D ultrasound in fetal cardiac scanning: a new look at the fetal heart, Ultrasound Obstet. Gynecol. 29 (2007) 81–95, https://doi.org/10.1002/uog.3912.
[92] Dr.F.-D. Lebit, P.Dr.R. Vladareanu, The Role of 4D Ultrasound in the Assessment of Fetal Behaviour, Maedica 6 (2011) 120–127.
[93] H. Hu, X. Zhu, C. Wang, L. Zhang, X. Li, S. Lee, Z. Huang, R. Chen, Z. Chen, C. Wang, Y. Gu, Y. Chen, Y. Lei, T. Zhang, N. Kim, Y. Guo, Y. Teng, W. Zhou, Y. Li, A. Nomoto, S. Sternini, Q. Zhou, M. Pharr, F.L. di Scalea, S. Xu, Stretchable ultrasonic transducer arrays for three-dimensional imaging on complex surfaces, Sci. Adv. 4 (2018) eaar3979, https://doi.org/10.1126/sciadv.aar3979.
[94] F. Wang, P. Jin, Y. Feng, J. Fu, P. Wang, X. Liu, Y. Zhang, Y. Ma, Y. Yang, A. Yang, X. Feng, Flexible Doppler ultrasound device for the monitoring of blood flow velocity, Sci. Adv. 7 (2021) eabi9283, https://doi.org/10.1126/sciadv.abi9283.
[95] H. Hu, H. Huang, M. Li, X. Gao, L. Yin, R. Qi, R.S. Wu, X. Chen, Y. Ma, K. Shi, C. Li, T.M. Maus, B. Huang, C. Lu, M. Lin, S. Zhou, Z. Lou, Y. Gu, Y. Chen, Y. Lei, X. Wang, R. Wang, W. Yue, X. Yang, Y. Bian, J. Mu, G. Park, S. Xiang, S. Cai, P. W. Corey, J. Wang, S. Xu, A wearable cardiac ultrasound imager, Nature 613 (2023) 667–675, https://doi.org/10.1038/s41586-022-05498-z.
[96] C. Wang, X. Li, H. Hu, L. Zhang, Z. Huang, M. Lin, Z. Zhang, Z. Yin, B. Huang, H. Gong, S. Bhaskaran, Y. Gu, M. Makihata, Y. Guo, Y. Lei, Y. Chen, C. Wang, Y. Li, T. Zhang, Z. Chen, A.P. Pisano, L. Zhang, Q. Zhou, S. Xu, Monitoring of the central blood pressure waveform via a conformal ultrasonic device, Nat. Biomed. Eng. 2 (2018) 687–695, https://doi.org/10.1038/s41551-018-0287-x.
[97] Z. Izadifar, Z. Izadifar, D. Chapman, P. Babyn, An introduction to high intensity focused ultrasound: systematic review on principles, devices, and clinical applications, J. Clin. Med 9 (2020) 460, https://doi.org/10.3390/jcm9020460.
[98] C.M. Moran, A.J.W. Thomson, Preclinical ultrasound imaging—a review of techniques and imaging applications, Front. Phys. 8 (2020) 124, https://doi.org/10.3389/fphy.2020.00124.
[99] J. Hausman, G. Pollock, Basic Science: Principles of Ultrasound: Obtaining an Image, Resolution, Depth, Frequency, Resonance, in: R.K. Banik (Ed.), Anesthesiology In-Training Exam Review: Regional Anesthesia and Chronic Pain, Springer International Publishing, Cham, 2022, pp. 3–8, https://doi.org/10.1007/978-3-030-87266-3_1.
[100] C.C. Moreno, Diagnostic ultrasound: physics and equipment, second edition, Acad. Radiol. 19 (2012) 774–775, https://doi.org/10.1016/j.acra.2012.02.017.
[101] M. Cikes, L. Tong, G.R. Sutherland, 'hooge Jan D, Ultrafast Cardiac Ultrasound Imaging, JACC: Cardiovasc. Imaging 7 (2014) 812–823, https://doi.org/10.1016/j.jcmg.2014.06.004.
[102] J.M. Sanches, A.F. Laine, J.S. Suri (Eds.), Ultrasound Imaging: Advances and Applications, Springer US, Boston, MA, 2012, https://doi.org/10.1007/978-1-4614-1180-2.
[103] O. Villemain, J. Robin, A. Bel, W. Kwiecinski, P. Bruneval, B. Arnal, émond M. R, M. Tanter, E. Messas, M. Pernot, Pulsed Cavitational Ultrasound Softening, JACC: Basic Transl. Sci. 2 (2017) 372–383, https://doi.org/10.1016/j.jacbts.2017.03.012.
[104] A.H. Chowdhury, B. Jafarizadeh, A.R. Baboukani, N. Pala, C. Wang, Monitoring and analysis of cardiovascular pulse waveforms using flexible capacitive and piezoresistive pressure sensors and machine learning perspective, Biosens. Bioelectron. 237 (2023) 115449, https://doi.org/10.1016/j.bios.2023.115449.
[105] Y. Huang, L. Zhao, M. Cai, J. Zhu, L. Wang, X. Chen, Y. Zeng, L. Zhang, J. Shi, C. F. Guo, Arteriosclerosis Assessment Based on Single-Point Fingertip Pulse Monitoring Using a Wearable Iontronic Sensor, Adv. Health Mater. 12 (2023) e2301838, https://doi.org/10.1002/adhm.202301838.
[106] S. Li, H. Wang, W. Ma, L. Qiu, K. Xia, Y. Zhang, H. Lu, M. Zhu, X. Liang, X.-E. Wu, H. Liang, Y. Zhang, Monitoring blood pressure and cardiac function without positioning via a deep learning–assisted strain sensor array, Sci. Adv. 9 (2023) eadh0615, https://doi.org/10.1126/sciadv.adh0615.
[107] P.H. Charlton, J. Allen, R. Bailon, S. Baker, J.A. Behar, F. Chen, G.D. Clifford, D. A. Clifton, H.J. Davies, C. Ding, X. Ding, J. Dunn, M. Elgendi, M. Ferdoushi, D. Franklin, E. Gil, M.F. Hassan, J. Hernesniemi, X. Hu, N. Ji, Y. Khan, S. Kontaxis, I. Korhonen, P.A. Kyriacou, P. Laguna, J. Lazaro, C. Lee, J. Levy, Y. Li, C. Liu, J. Liu, L. Lu, D.P. Mandic, V. Marozas, E. Mejia-Mejia, R. Mukkamala, M. Nitzan, T. Pereira, C.C.Y. Poon, J.C. Ramella-Roman, H. Saarinen, M.M.H. Shandhi, H. Shin, G. Stansby, T. Tamura, A. Vehkaoja, W.K. Wang, Y.-T. Zhang, N. Zhao, D. Zheng, T. Zhu, The 2023 wearable photoplethysmography roadmap, Physiol. Meas. 44 (2023) 111001, https://doi.org/10.1088/1361-6579/acead2.
[108] R. Ferizoli, P. Karimpour, J.M. May, P.A. Kyriacou, Arterial stiffness assessment using PPG feature extraction and significance testing in an in vitro cardiovascular system, Sci. Rep. 14 (2024) 2024, https://doi.org/10.1038/s41598-024-51395-y.
[109] B. Anbuselvam, B.M. Gunasekaran, S. Srinivasan, M. Ezhilan, V. Rajagopal, N. Nesakumar, Wearable biosensors in cardiovascular disease, Clin. Chim. Acta 561 (2024) 119766, https://doi.org/10.1016/j.cca.2024.119766.
[110] H. Gao, X. Wang, Z. Chen, M. Wu, J. Li, C. Liu, ECG-CL: A Comprehensive Electrocardiogram Interpretation Method Based on Continual Learning, IEEE J. Biomed. Health Inform. 27 (2023) 5225–5236, https://doi.org/10.1109/JBHI.2023.3315715.
[111] A. Di Costanzo, C.A.M. Spaccarotella, G. Esposito, C. Indolfi, An artificial intelligence analysis of electrocardiograms for the clinical diagnosis of cardiovascular diseases: a narrative review, J. Clin. Med. 13 (2024) 1033, https://doi.org/10.3390/jcm13041033.
[112] X. Pan, C. Wang, Y. Yu, N. Reljin, D.D. McManus, C.E. Darling, K.H. Chon, Y. Mendelson, K. Lee, Deep cross-modal feature learning applied to predict acutely decompensated heart failure using in-home collected electrocardiography and transthoracic bioimpedance, Artif. Intell. Med. 140 (2023) 102548, https://doi.org/10.1016/j.artmed.2023.102548.
[113] K. Sel, D. Osman, N. Huerta, A. Edgar, R.I. Pettigrew, R. Jafari, Continuous cuffless blood pressure monitoring with a wearable ring bioimpedance device, Npj Digit. Med. 6 (2023) 59, https://doi.org/10.1038/s41746-023-00796-w.
[114] A. Hossein, E. Abdessater, P. Balali, E. Cosneau, D. Gorlier, J. Rabineau, A. Almorad, V. Faoro, P. van de Borne, Smartphone-Derived Seismocardiography: Robust Approach for Accurate Cardiac Energy Assessment in Patients with Various Cardiovascular Conditions, Sensors 24 (2024) 2139, https://doi.org/10.3390/s24072139.
[115] T.L. Steffensen, F.E. Schjerven, H.M. Flade, I. Kirkeby-Garstad, E. Ingestroem, F. S. Solberg, M. Steinert, Wrist ballistocardiography and invasively recorded blood pressure in healthy volunteers during reclining bike exercise, Front. Physiol. 14 (2023) 1189732, https://doi.org/10.3389/fphys.2023.1189732.
[116] S. Feng, X. Wu, A. Bao, G. Lin, P. Sun, H. Cen, S. Chen, Y. Liu, W. He, Z. Pang, H. Zhang, Machine learning-aided detection of heart failure (LVEF=49%) by using ballistocardiography and respiratory effort signals, Front. Physiol. 13 (2023) 1068824, https://doi.org/10.3389/fphys.2022.1068824.
[117] L. Artyszuk, E. Blazejowska, Z. Danielecka, J. Jurek, E. Olek, P. Abramczyk, Peripheral atherosclerosis evaluation through ultrasound: a promising diagnostic tool for coronary artery disease, Echocardiogr. -J. Cardiovasc. Ultrasound Allied Tech. 40 (2023) 841–851, https://doi.org/10.1111/echo.15652.
[118] L. Gan, Z. Wu, Ultrasonography Techniques for Atherosclerosis Assessment: A Narrative Review, Iran. Red. Crescent Med. J. 25 (2023) e2599, https://doi.org/10.32592/ircmj.2023.25.7.2599.
[119] C. Xue, S.S. Kowshik, D. Lteif, S. Puducheri, V.H. Jasodanand, O.T. Zhou, A. S. Walia, O.B. Guney, J.D. Zhang, S.T. Pham, A. Kaliaev, V.C. Andreu-Arasa, B. C. Dwyer, C.W. Farris, H. Hao, S. Kedar, A.Z. Mian, D.L. Murman, S.A. O'Shea, A. B. Paul, S. Rohatgi, M.-H. Saint-Hilaire, E.A. Sartor, B.N. Setty, J.E. Small, A. Swaminathan, O. Taraschenko, J. Yuan, Y. Zhou, S. Zhu, C. Karjadi, T.F. Alvin Ang, S.A. Bargal, B.A. Plummer, K.L. Poston, M. Ahangaran, R. Au, V. B. Kolachalama, AI-based differential diagnosis of dementia etiologies on

multimodal data, Nat. Med (2024) 1–13, https://doi.org/10.1038/s41591-024-03118-z.
[120] J. Shao, J. Ma, Y. Yu, S. Zhang, W. Wang, W. Li, C. Wang, A multimodal integration pipeline for accurate diagnosis, pathogen identification, and prognosis prediction of pulmonary infections, Innovation 5 (2024), https://doi.org/10.1016/j.xinn.2024.100648.
[121] H.-Y. Zhou, Y. Yu, C. Wang, S. Zhang, Y. Gao, J. Pan, J. Shao, G. Lu, K. Zhang, W. Li, A transformer-based representation-learning model with unified processing of multimodal input for clinical diagnostics, Nat. Biomed. Eng. 7 (2023) 743–755, https://doi.org/10.1038/s41551-023-01045-x.
[122] S. Wu, Y. Liu, Y. Tang, X. Jiang, L. Liu, X. Liu, J. Cao, Y. Liu, Dielectric modulation strategy of carbon nanotube field effect transistors based pressure sensor: towards precise monitoring of human pulse, Nanotechnology 34 (2023) 315501, https://doi.org/10.1088/1361-6528/acd19a.
[123] S. Abdullah, A. Kristoffersson, Machine learning approaches for cardiovascular hypertension stage estimation using photoplethysmography and clinical features, Front. Cardiovasc. Med. 10 (2023) 1285066, https://doi.org/10.3389/fcvm.2023.1285066.
[124] L. Neri, M.T. Oberdier, K.C.J. van Abeelen, L. Menghini, E. Tumarkin, H. Tripathi, S. Jaipalli, A. Orro, N. Paolocci, I. Gallelli, M. Dall'Olio, A. Beker, R.T. Carrick, C. Borghi, H.R. Halperin, Electrocardiogram monitoring wearable devices and artificial-intelligence-enabled diagnostic capabilities: a review, Sensors 23 (2023) 4805, https://doi.org/10.3390/s23104805.
[125] L. Gan, X. Yin, J. Huang, B. Jia, Transcranial Doppler analysis based on computer and artificial intelligence for acute cerebrovascular disease, Math. Biosci. Eng. 20 (2023) 1695–1715, https://doi.org/10.3934/mbe.2023077.
[126] S. Shelke, K. Veerubhotla, Y. Lee, C.H. Lee, Telehealth of cardiac devices for CVD treatment, Biotechnol. Bioeng. 121 (2024) 823–834, https://doi.org/10.1002/bit.28637.
[127] M. Ullah, S. Hamayun, A. Wahab, S.U. Khan, M.U. Rehman, Z.Ul Haq, K. U. Rehman, A. Ullah, A. Mehreen, U.A. Awan, M. Qayum, M. Naeem, Smart technologies used as smart tools in the management of cardiovascular disease and their future perspective, Curr. Probl. Cardiol. 48 (2023) 101922, https://doi.org/10.1016/j.cpcardiol.2023.101922.
[128] M. Narkhede, A. Pardeshi, R. Bhagat, G. Dharme, Review on Emerging Therapeutic Strategies for Managing Cardiovascular Disease, Curr. Cardiol. Rev. 20 (2024) 86–100, https://doi.org/10.2174/011573403X299265240405080030.
[129] R. Khera, E.K. Oikonomou, G.N. Nadkarni, J.R. Morley, J. Wiens, A.J. Butte, E. J. Topol, Transforming cardiovascular care with artificial intelligence: from discovery to practice, J. Am. Coll. Cardiol. 84 (2024) 97–114, https://doi.org/10.1016/j.jacc.2024.05.003.
[130] Y. Wang, P. Tan, Y. Wu, D. Luo, Z. Li, Artificial intelligence-enhanced skin-like sensors based on flexible nanogenerators, VIEW (2022) 20220026, https://doi.org/10.1002/VIW.20220026.
[131] B. Sandeep, X. Liu, X. Huang, X. Wang, L. Mao, Z. Xiao, Feasibility of artificial intelligence its current status, clinical applications, and future direction in cardiovascular disease, Curr. Probl. Cardiol. 49 (2024) 102349, https://doi.org/10.1016/j.cpcardiol.2023.102349.
[132] X. Sun, Y. Yin, Q. Yang, T. Huo, Artificial intelligence in cardiovascular diseases: diagnostic and therapeutic perspectives, Eur. J. Med. Res. 28 (2023) 242, https://doi.org/10.1186/s40001-023-01065-y.
[133] J.-U. Park, D.-W. Kang, U. Erdenebayar, Y.-J. Kim, K.-C. Cha, K.-J. Lee, Estimation of arterial blood pressure based on artificial intelligence using single earlobe photoplethysmography during cardiopulmonary resuscitation, J. Med Syst. 44 (2019) 18, https://doi.org/10.1007/s10916-019-1514-z.
[134] M. Moshawrab, M. Adda, A. Bouzouane, H. Ibrahim, A. Raad, Smart wearables for the detection of cardiovascular diseases: a systematic literature review, Sensors 23 (2023) 828, https://doi.org/10.3390/s23020828.
[135] J.-H. Lee, K.H. Cho, K. Cho, Emerging Trends in Soft Electronics: Integrating Machine Intelligence with Soft Acoustic/Vibration Sensors, Adv. Mater. 35 (2023) 2209673, https://doi.org/10.1002/adma.202209673.
[136] A. Hughes, M.M.H. Shandhi, H. Master, J. Dunn, E. Brittain, Wearable devices in cardiovascular medicine, Circ. Res. 132 (2023) 652–670, https://doi.org/10.1161/CIRCRESAHA.122.322389.
[137] A.-T. Shumba, T. Montanaro, I. Sergi, A. Bramanti, M. Ciccarelli, A. Rispoli, A. Carrizzo, M. De Vittorio, L. Patrono, Wearable technologies and AI at the far edge for chronic heart failure prevention and management: a systematic review and prospects, Sensors 23 (2023) 6896, https://doi.org/10.3390/s23156896.
[138] A. Mizuno, S. Changolkar, M.S. Patel, Wearable devices to monitor and reduce the risk of cardiovascular disease: evidence and opportunities, Annu. Rev. Med. 72 (2021) 459–471, https://doi.org/10.1146/annurev-med-050919-031534.
[139] Z. Jiang, V. Van Zoest, W. Deng, E.C.H. Ngai, J. Liu, Leveraging machine learning for disease diagnoses based on wearable devices: a survey, IEEE Internet Things J. 10 (2023) 21959–21981, https://doi.org/10.1109/JIOT.2023.3313158.
[140] S. Panesar, Y. Cagle, D. Chander, J. Morey, J. Fernandez-Miranda, M. Kliot, Artificial intelligence and the future of surgical robotics, Ann. Surg. 270 (2019) 223, https://doi.org/10.1097/SLA.0000000000003262.
[141] Y. Zou, A. Libanori, J. Xu, A. Nashalian, J. Chen, Triboelectric nanogenerator enabled smart shoes for wearable electricity generation, Research 2020 (2020), https://doi.org/10.34133/2020/7158953.
[142] Y. Su, W. Li, L. Yuan, C. Chen, H. Pan, G. Xie, G. Conta, S. Ferrier, X. Zhao, G. Chen, H. Tai, Y. Jiang, J. Chen, Piezoelectric fiber composites with polydopamine interfacial layer for self-powered wearable biomonitoring, Nano Energy 89 (2021) 106321, https://doi.org/10.1016/j.nanoen.2021.106321.
[143] M. Kaltenbrunner, T. Sekitani, J. Reeder, T. Yokota, K. Kuribara, T. Tokuhara, M. Drack, R. Schwödiauer, I. Graz, S. Bauer-Gogonea, S. Bauer, T. Someya, An ultra-lightweight design for imperceptible plastic electronics, Nature 499 (2013) 458–463, https://doi.org/10.1038/nature12314.
[144] H. Jia, Y. Gao, J. Zhou, J. Li, C.K. Yiu, W. Park, Z. Yang, X. Yu, A deep learning-assisted skin-integrated pulse sensing system for reliable pulse monitoring and cardiac function assessment, Nano Energy 127 (2024) 109796, https://doi.org/10.1016/j.nanoen.2024.109796.
[145] C. Pang, G.-Y. Lee, T. Kim, S.M. Kim, H.N. Kim, S.-H. Ahn, K.-Y. Suh, A flexible and highly sensitive strain-gauge sensor using reversible interlocking of nanofibres, Nat. Mater. 11 (2012) 795–801, https://doi.org/10.1038/NMAT3380.
[146] T. Liu, G. Gou, F. Gao, P. Yao, H. Wu, Y. Guo, M. Yin, J. Yang, T. Wen, M. Zhao, T. Li, G. Chen, J. Sun, T. Ma, J. Cheng, Z. Qi, J. Chen, J. Wang, M. Han, Z. Fang, Y. Gao, C. Liu, N. Xue, Multichannel Flexible Pulse Perception Array for Intelligent Disease Diagnosis System, ACS Nano 17 (2023) 5673–5685, https://doi.org/10.1021/acsnano.2c11897.
[147] C. Pang, J.H. Koo, A. Nguyen, J.M. Caves, M.-G. Kim, A. Chortos, K. Kim, P. J. Wang, J.B.-H. Tok, Z. Bao, Highly skin-conformal microhairy sensor for pulse signal amplification, Adv. Mater. 27 (2015) 634–640, https://doi.org/10.1002/adma.201403807.
[148] H. Xu, L. Gao, H. Zhao, H. Huang, Y. Wang, G. Chen, Y. Qin, N. Zhao, D. Xu, L. Duan, X. Li, S. Li, Z. Luo, W. Wang, Y. Lu, Stretchable and anti-impact iontronic pressure sensor with an ultrabroad linear range for biophysical monitoring and deep learning-aided knee rehabilitation, Micro Nanoeng. 7 (2021) 1–11, https://doi.org/10.1038/s41378-021-00318-2.
[149] P. Tan, Y. Xi, S. Chao, D. Jiang, Z. Liu, Y. Fan, Z. Li, An artificial intelligence-enhanced blood pressure monitor wristband based on piezoelectric nanogenerator, Biosensors 12 (2022) 234, https://doi.org/10.3390/bios12040234.
[150] X. Ran, F. Luo, Z. Lin, Z. Zhu, C. Liu, B. Chen, Blood pressure monitoring via double sandwich-structured triboelectric sensors and deep learning models, Nano Res 15 (2022) 5500–5509, https://doi.org/10.1007/s12274-022-4172-2.
[151] C. Yao, T. Sun, S. Huang, M. He, B. Liang, Z. Shen, X. Huang, Z. Liu, H. Wang, F. Liu, H.-J. Chen, X. Xie, Personalized machine learning-coupled nanopillar triboelectric pulse sensor for cuffless blood pressure continuous monitoring, ACS Nano 17 (2023) 24242–24258, https://doi.org/10.1021/acsnano.3c09766.
[152] Y. Zhou, X. Zhao, J. Xu, Y. Fang, G. Chen, Y. Song, S. Li, J. Chen, Giant magnetoelastic effect in soft systems for bioelectronics, Nat. Mater. 20 (2021) 1670–1676, https://doi.org/10.1038/s41563-021-01093-1.
[153] J. Li, H. Jia, J. Zhou, X. Huang, L. Xu, S. Jia, Z. Gao, K. Yao, D. Li, B. Zhang, Y. Liu, Y. Huang, Y. Hu, G. Zhao, Z. Xu, J. Li, C.K. Yiu, Y. Gao, M. Wu, Y. Jiao, Q. Zhang, X. Tai, R.H. Chan, Y. Zhang, X. Ma, X. Yu, Thin, soft, wearable system for continuous wireless monitoring of artery blood pressure, Nat. Commun. 14 (2023) 5009, https://doi.org/10.1038/s41467-023-40763-3.
[154] H.U. Chung, B.H. Kim, J.Y. Lee, J. Lee, Z. Xie, E.M. Ibler, K. Lee, A. Banks, J. Y. Jeong, J. Kim, C. Ogle, D. Grande, Y. Yu, H. Jang, P. Assem, D. Ryu, J.W. Kwak, M. Namkoong, J.B. Park, Y. Lee, D.H. Kim, A. Ryu, J. Jeong, K. You, B. Ji, Z. Liu, Q. Huo, X. Feng, Y. Deng, Y. Xu, K.-I. Jang, J. Kim, Y. Zhang, R. Ghaffari, C. M. Rand, M. Schau, A. Hamvas, D.E. Weese-Mayer, Y. Huang, S.M. Lee, C.H. Lee, N.R. Shanbhag, A.S. Paller, S. Xu, J.A. Rogers, Binodal, wireless epidermal electronic systems with in-sensor analytics for neonatal intensive care, Science 363 (2019) eaau0780, https://doi.org/10.1126/science.aau0780.
[155] S.-H. Liu, R.-X. Li, J.-J. Wang, W. Chen, C.-H. Su, Classification of photoplethysmographic signal quality with deep convolution neural networks for accurate measurement of cardiac stroke volume, Appl. Sci. 10 (2020) 4612, https://doi.org/10.3390/app10134612.
[156] S. Moscato, S. Lo Giudice, G. Massaro, L. Chiari, Wrist Photoplethysmography Signal Quality Assessment for Reliable Heart Rate Estimate and Morphological Analysis, Sensors 22 (2022) 5831, https://doi.org/10.3390/s22155831.
[157] C.-F. Wang, T.-Y. Wang, P.-H. Kuo, H.-L. Wang, S.-Z. Li, C.-M. Lin, S.-C. Chan, T.-Y. Liu, Y.-C. Lo, S.-H. Lin, Y.-Y. Chen, Upper-arm photoplethysmographic sensor with one-time calibration for long-term blood pressure monitoring, Biosens.-Basel 13 (2023) 321, https://doi.org/10.3390/bios13030321.
[158] J. Lai, H. Tan, J. Wang, L. Ji, J. Guo, B. Han, Y. Shi, Q. Feng, W. Yang, Practical intelligent diagnostic algorithm for wearable 12-lead ECG via self-supervised learning on large-scale dataset, Nat. Commun. 14 (2023) 3741, https://doi.org/10.1038/s41467-023-39472-8.
[159] D. Son, J. Kang, O. Vardoulis, Y. Kim, N. Matsuhisa, J.Y. Oh, J.W. To, J. Mun, T. Katsumata, Y. Liu, A.F. McGuire, M. Krason, F. Molina-Lopez, J. Ham, U. Kraft, Y. Lee, Y. Yun, J.B.-H. Tok, Z. Bao, An integrated self-healable electronic skin system fabricated via dynamic reconstruction of a nanostructured conducting network, Nat. Nanotech 13 (2018) 1057–1065, https://doi.org/10.1038/s41565-018-0244-6.
[160] Y. Chen, C. Zhang, C. Liu, Y. Wang, X. Wan, Atrial fibrillation detection using a feedforward neural network, J. Med. Biol. Eng. 42 (2022) 63–73, https://doi.org/10.1007/s40846-022-00681-z.
[161] W. Li, Y.M. Tang, K.M. Yu, S. To, SLC-GAN: An automated myocardial infarction detection model based on generative adversarial networks and convolutional neural networks with single-lead electrocardiogram synthesis, Inf. Sci. 589 (2022) 738–750, https://doi.org/10.1016/j.ins.2021.12.083.
[162] D. Kireev, K. Sel, B. Ibrahim, N. Kumar, A. Akbari, R. Jafari, D. Akinwande, Continuous cuffless monitoring of arterial blood pressure via graphene bioimpedance tattoos, Nat. Nanotechnol. 17 (2022) 864–870, https://doi.org/10.1038/s41565-022-01145-w.
[163] K. Sel, D. Osman, R. Jafari, Non-invasive cardiac and respiratory activity assessment from various human body locations using bioimpedance, Ieee Open J. Eng. Med 2 (2021) 210–217, https://doi.org/10.1109/OJEMB.2021.3085482.

[164] J.S. Chiu, C.F. Chong, Y.F. Lin, C.C. Wu, Y.F. Wang, Y.C. Li, Applying an artificial neural network to predict total body water in hemodialysis patients, Am. J. Nephrol. 25 (2005) 507–513, https://doi.org/10.1159/000088279.

[165] A. Nana, J.M.D. Staynor, S. Arlai, A. El-Sallam, N. Dhungel, M.K. Smith, Agreement of anthropometric and body composition measures predicted from 2D smartphone images and body impedance scales with criterion methods, Obes. Res. Clin. Pract. 16 (2022) 37–43, https://doi.org/10.1016/j.orcp.2021.12.006.

[166] Y. Liu, J.J.S. Norton, R. Qazi, Z. Zou, K.R. Ammann, H. Liu, L. Yan, P.L. Tran, K.-I. Jang, J.W. Lee, D. Zhang, K.A. Kilian, S.H. Jung, T. Bretl, J. Xiao, M.J. Slepian, Y. Huang, J.-W. Jeong, J.A. Rogers, Epidermal mechano-acoustic sensing electronics for cardiovascular diagnostics and human-machine interfaces, Sci. Adv. 2 (2016) e1601185, https://doi.org/10.1126/sciadv.1601185.

[167] S.H. Lee, Y.-S. Kim, M.-K. Yeo, M. Mahmood, N. Zavanelli, C. Chung, J.Y. Heo, Y. Kim, S.-S. Jung, W.-H. Yeo, Fully portable continuous real-time auscultation with a soft wearable stethoscope designed for automated disease diagnosis, Sci. Adv. 8 (2022) eabo5867, https://doi.org/10.1126/sciadv.abo5867.

[168] W. Yan, G. Noel, G. Loke, E. Meiklejohn, T. Khudiyev, J. Marion, G. Rui, J. Lin, J. Cherston, A. Sahasrabudhe, J. Wilbert, I. Wicaksono, R.W. Hoyt, A. Missakian, L. Zhu, C. Ma, J. Joannopoulos, Y. Fink, Single fibre enables acoustic fabrics via nanometre-scale vibrations, Nature 603 (2022) 616–623, https://doi.org/10.1038/s41586-022-04476-9.

[169] M.M.H. Shandhi, J. Fan, J.A. Heller, M. Etemadi, L. Klein, O.T. Inan, Estimation of Changes in Intracardiac Hemodynamics Using Wearable Seismocardiography and Machine Learning in Patients With Heart Failure: A Feasibility Study, IEEE Trans. Biomed. Eng. 69 (2022) 2443–2455, https://doi.org/10.1109/TBME.2022.3147066.

[170] J. Yan, B. Huang, J. Tonko, M. Toulemonde, J. Hansen-Shearer, Q. Tan, K. Riemer, K. Ntagiantas, R.A. Chowdhury, P.D. Lambiase, R. Senior, M.-X. Tang, Transthoracic ultrasound localization microscopy of myocardial vasculature in patients, Nat. Biomed. Eng. 8 (2024) 689–700, https://doi.org/10.1038/s41551-024-01206-6.

[171] C. Xiao, Z. Li, J. Lu, J. Wang, H. Zheng, Z. Bi, M. Chen, R. Mao, M. Lu, A new deep learning method for displacement tracking from ultrasound RF signals of vascular walls, Comput. Med. Imaging Graph. 87 (2021) 101819, https://doi.org/10.1016/j.compmedimag.2020.101819.

[172] Y. Bai, H. Meng, Z. Li, Z.L. Wang, Degradable piezoelectric biomaterials for medical applications, Med Mat. 1 (2024) 40, https://doi.org/10.1097/mm9.0000000000000002.

[173] Y. Bai, H. Wang, Y. Xue, Y. Pan, J.-T. Kim, X. Ni, T.-L. Liu, Y. Yang, M. Han, Y. Huang, J.A. Rogers, X. Ni, A dynamically reprogrammable surface with self-evolving shape morphing, Nature 609 (2022) 701, https://doi.org/10.1038/s41586-022-05061-w.

[174] J. Jumper, R. Evans, A. Pritzel, T. Green, M. Figurnov, O. Ronneberger, K. Tunyasuvunakool, R. Bates, A. Zidek, A. Potapenko, A. Bridgland, C. Meyer, S. A.A. Kohl, A.J. Ballard, A. Cowie, B. Romera-Paredes, S. Nikolov, R. Jain, J. Adler, T. Back, S. Petersen, D. Reiman, E. Clancy, M. Zielinski, M. Steinegger, M. Pacholska, T. Berghammer, S. Bodenstein, D. Silver, O. Vinyals, A.W. Senior, K. Kavukcuoglu, P. Kohli, D. Hassabis, Highly accurate protein structure prediction with AlphaFold, Nature 596 (2021) 583, https://doi.org/10.1038/s41586-021-03819-2.

[175] S. Molesky, Z. Lin, A.Y. Piggott, W. Jin, J. Vuckovic, A.W. Rodriguez, Inverse design in nanophotonics, Nat. Photonics 12 (2018) 659–670, https://doi.org/10.1038/s41566-018-0246-9.

[176] Z. Fan, Y. Yang, F. Zhang, Z. Xu, H. Zhao, T. Wang, H. Song, Y. Huang, J. A. Rogers, Y. Zhang, Inverse design strategies for 3D surfaces formed by mechanically guided assembly, Adv. Mater. 32 (2020) 1908424, https://doi.org/10.1002/adma.201908424.

[177] Y. Lu, D. Kong, G. Yang, R. Wang, G. Pang, H. Luo, H. Yang, K. Xu, Machine learning-enabled tactile sensor design for dynamic touch decoding, Adv. Sci. 10 (2023), https://doi.org/10.1002/advs.202303949.

[178] N. Bai, L. Wang, Y. Xue, Y. Wang, X. Hou, G. Li, Y. Zhang, M. Cai, L. Zhao, F. Guan, X. Wei, C.F. Guo, Graded interlocks for iontronic pressure sensors with high sensitivity and high linearity over a broad range, ACS Nano 16 (2022) 4338–4347, https://doi.org/10.1021/acsnano.1c10535.

[179] P. Lu, L. Wang, P. Zhu, J. Huang, Y. Wang, N. Bai, Y. Wang, G. Li, J. Yang, K. Xie, J. Zhang, B. Yu, Y. Dai, C.F. Guo, Iontronic pressure sensor with high sensitivity and linear response over a wide pressure range based on soft micropillared electrodes, Sci. Bull. 66 (2021) 1091–1100, https://doi.org/10.1016/j.scib.2021.02.019.

[180] Z. Liu, M. Cai, S. Hong, J. Shi, S. Xie, C. Liu, H. Du, J.D. Morin, G. Li, L. Wang, H. Wang, K. Tang, N.X. Fang, C.F. Guo, Data-driven inverse design of flexible pressure sensors, Proc. Natl. Acad. Sci. 121 (2024) e2320222121, https://doi.org/10.1073/pnas.2320222121.

[181] J. Kim, M. Lee, H.J. Shim, R. Ghaffari, H.R. Cho, D. Son, Y.H. Jung, M. Soh, C. Choi, S. Jung, K. Chu, D. Jeon, S.-T. Lee, J.H. Kim, S.H. Choi, T. Hyeon, D.-H. Kim, Stretchable silicon nanoribbon electronics for skin prosthesis, Nat. Commun. 5 (2014) 5747, https://doi.org/10.1038/ncomms6747.

[182] R. Xu, J.W. Lee, T. Pan, S. Ma, J. Wang, J.H. Han, Y. Ma, J.A. Rogers, Y. Huang, Designing Thin, Ultrastretchable Electronics with Stacked Circuits and Elastomeric Encapsulation Materials, Adv. Funct. Mater. 27 (2017) 1604545, https://doi.org/10.1002/adfm.201604545.

[183] R.-H. Kim, D.-H. Kim, J. Xiao, B.H. Kim, S.-I. Park, B. Panilaitis, R. Ghaffari, J. Yao, M. Li, Z. Liu, V. Malyarchuk, D.G. Kim, A.-P. Le, R.G. Nuzzo, D.L. Kaplan, F.G. Omenetto, Y. Huang, Z. Kang, J.A. Rogers, Waterproof AlInGaP optoelectronics on stretchable substrates with applications in biomedicine and robotics, Nat. Mater. 9 (2010) 929–937, https://doi.org/10.1038/nmat2879.

[184] Q. Zheng, Q. Tang, Z.L. Wang, Z. Li, Self-powered cardiovascular electronic devices and systems, Nat. Rev. Cardiol. 18 (2021) 7–21, https://doi.org/10.1038/s41569-020-0426-4.

[185] A. Krizhevsky, I. Sutskever, G.E. Hinton, ImageNet classification with deep convolutional neural networks, Commun. ACM 60 (2017) 84–90, https://doi.org/10.1145/3065386.

[186] S. Lee, C.-H. Park, J.-H. Chang, Improved gaussian mixture regression based on pseudo feature generation using bootstrap in blood pressure estimation, IEEE Trans. Ind. Inform. 12 (2016) 2269–2280, https://doi.org/10.1109/TII.2015.2484278.

[187] S. Lee, A. Ahmad, G. Jeon, Combining bootstrap aggregation with support vector regression for small blood pressure measurement, J. Med Syst. 42 (2018) 63, https://doi.org/10.1007/s10916-018-0913-x.

[188] A. Argha, J. Wu, S.W. Su, B.G. Celler, Blood pressure estimation from beat-by-beat time-domain features of oscillometric waveforms using deep-neural-network classification models, IEEE Access 7 (2019) 113427–113439, https://doi.org/10.1109/ACCESS.2019.2933498.

[189] P.A. Noseworthy, E.S. Kaufman, L.Y. Chen, M.K. Chung, M.S.V. Elkind, J. A. Joglar, M.A. Leal, P.J. McCabe, S.D. Pokorney, X. Yao, null null, Subclinical and Device-Detected Atrial Fibrillation: Pondering the Knowledge Gap: A Scientific Statement From the American Heart Association, Circulation 140 (2019), https://doi.org/10.1161/CIR.0000000000000740.

[190] K.R. Foster, J. Torous, The opportunity and obstacles for smartwatches and wearable sensors, IEEE Pulse 10 (2019) 22–25, https://doi.org/10.1109/MPULS.2018.2885832.

[191] V.A. Goodyear, Social media, apps and wearable technologies: navigating ethical dilemmas and procedures, Qual. Res. Sport, Exerc. Health 9 (2017) 285–302, https://doi.org/10.1080/2159676X.2017.1303790.

[192] D. Fresilli, N. Di Leo, O. Martinelli, L. Di Marzo, P. Pacini, V. Dolcetti, G. Del Gaudio, F. Canni, L.I. Ricci, C. De Vito, C. Caiazzo, R. Carletti, C. Di Gioia, I. Carbone, S.B. Feinstein, C. Catalano, V. Cantisani, 3D-Arterial analysis software and CEUS in the assessment of severity and vulnerability of carotid atherosclerotic plaque: a comparison with CTA and histopathology, Radio. Med 127 (2022) 1254–1269, https://doi.org/10.1007/s11547-022-01551-z.

Yiqian Wang received his bachelor's degree in process equipment and control engineering from Taiyuan University of technology in 2019. At present, he is studying for a doctor's degree in physics at the school of physical science and engineering technology of Guangxi University. His interests include wearable electronic medical devices, artificial intelligence and bionic adaptive sensor.

Yang Zou received his Bachelor's degree from Beihang University in 2016, and Doctor's Degree in Nanoscience and Technology from University of Chinese Academy of Sciences in 2021. He is now a postdoctoral fellow at the Beijing Institute of Technology. His research interests mainly focus on wearable energy harvesters, biosensors, nanogenerators, and bionic electronics.

Prof. Zhou Li received his Doctor's Degree from Peking University in 2010, and a bachelor's degree from Wuhan University in 2004. He studied at the Georgia Institute of Technology from 2007 to 2009 as a visiting PhD student. Currently, he is principal investigator and group leader of Nanoenergy and Biosystem Lab (NBL) in Beijing Institute of Nanoenergy and Nanosystems, Chinese Academy of Sciences. His research focuses on the advancement of bioelectronic and medical devices, namely in the areas of wearable and implantable electronic health monitoring and therapy devices, biosensors, biodegradable electronics, and biomechanical investigations.