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# Non-invasive cardiovascular and vital signs monitoring techniques: review, challenges, and perspectives

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ABSTRACT

Cardiovascular diseases are the leading cause of global fatalities, necessitating effective diagnostic solutions. Traditional methods, while valuable, often require invasive procedures or require subjects to remain stationary, limiting their real-time monitoring capability in dynamic environments. This article reviews the emerging field of contactless and distraction-free cardiovascular monitoring, which offers distraction-free, flexible, and user-friendly alternatives for enhanced accessibility. We examine various techniques, including radar-based methods, optical measurements, ballistocardiography, contactless electrocardiogram (ECG), and wearable devices, comparing their working principles, advantages, and limitations against traditional diagnosis methods. The novelty of this review lies in its comprehensive evaluation of these methods across eight key dimensions, including application breadth, time efficiency, reliability, distraction-free operation, safety, bandwidth, information value, and working distance. Another new perspective involves how advanced hardware, digital filters, and artificial intelligence (AI)-driven signal processing methods address challenges associated with relatively poor signal quality. Additionally, this article discusses these techniques' key values on healthcare, challenges, and emerging opportunities.

## 1. Introduction

Cardiovascular disease accounts for a significant portion of global mortality, responsible for 32 % of deaths worldwide according to the World Health Organization (WHO) [1]. As a result, cardiovascular and vital monitoring has been a highly focused point of interest for several decades. Cardiovascular assessment comes with a wide range of parameters, which can be measured with different techniques, primarily targeting mechanical signs, circulation dynamics, and electrical activities of the heart. For example, cardiac structural abnormalities can be initially screened through phonocardiogram (PCG) or auscultation [2] and further confirmed via diagnostic imaging techniques like echocardiogram (ultrasound) or chest X-rays. Cardiac performance dynamics are typically assessed via blood pressure measurement, ultrasound, or impedance cardiography (ICG). Meanwhile, the heart's electrical activities are most accurately evaluated using an electrocardiogram (ECG) [3].

Proper monitoring and assessment of these parameters are crucial for the prevention and timely intervention of cardiac diseases. Cardiovascular abnormalities are often reflected in these vital signs, making continuous and accurate measurements essential not only for assessing cardiovascular health but also for predicting certain cardiovascular diseases and events. However, the above traditional monitoring methods are primarily employed in clinical settings, requiring trained medical personnel and specialised equipment. These methods also impose several limitations on patients, such as the need for sensors and wires that can cause discomfort [4], even leading to allergic reactions over long periods [5], and the requirement for patients to remain in specific positions during monitoring [6]. These constraints limit the use of traditional monitoring techniques in dynamic or real-life environments, particularly during operative procedures such as working, driving, or gaming. Furthermore, some traditional medical methods of cardiovascular monitoring are highly invasive and can even pose risks to the patient. For instance, radiological imaging involves exposure to intense electromagnetic waves or ionising radiation, which can be harmful, especially with repeated use [7]. Invasive techniques, such as blood pressure monitoring through catheterisation or cardiovascular catheterisation itself, often require surgical procedures or the insertion of catheters into the body, increasing the potential for complications [8]. As a result, there is a growing demand for novel approaches to reduce

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invasiveness, reduce distractions and enhance the user experience, enabling more accessible and patient-friendly cardiovascular monitoring solutions. It should be noted that the intention is not to replace traditional techniques used in clinical settings, where they hold significant diagnostic value, but rather to extend heart monitoring to a wider range of environments.

The advancement of mobile devices and wireless technologies has led to significant breakthroughs in emerging innovative measurement techniques. Current emerging distraction-free heart monitoring methods can be broadly categorised into two areas: wearable smart devices [9] and contactless monitoring. Wearable devices currently dominate the field and are widely used, while contactless approaches are still in active research and development. These technologies offer several advantages over traditional medical devices, including greater accessibility, enhanced user experience, reduced distractions, and the ability to operate without the need for medical professionals. Despite their convenience, these technologies are not typically used for diagnostic purposes or approved for professional medical diagnoses. This is largely due to their susceptibility to interference and relatively lower reliability and accuracy. Depending on the specific implementation, these methods can be affected by various artefacts, such as environmental fluctuations, vibrations, and user movement, limiting their effectiveness in clinical settings.

This review provides the first comprehensive and systematic synthesis of emerging contactless and distraction-free cardiovascular monitoring techniques, a field that has so far remained fragmented and under-reviewed. While traditional cardiovascular monitoring methods are well established and extensively studied, newer approaches are typically only discussed in comparison to conventional techniques, without a broader perspective on their principles, advantages, and limitations. By analysing the working mechanisms of these methods, positioning them in relation to traditional approaches, and evaluating their attributes across multiple key dimensions, this paper offers a holistic view of their strengths and weaknesses. Furthermore, it highlights the challenges, opportunities, and future directions of contactless cardiovascular monitoring, providing valuable insights for researchers seeking an overview of the field, comparative analysis, or a foundation for advancing further research in this emerging area.

## 2. Methodology

A cardiovascular measurement and monitoring system typically combines a sensing device with an algorithmic protocol that acquires one or more inputs from specific sensors, processes and analyses the

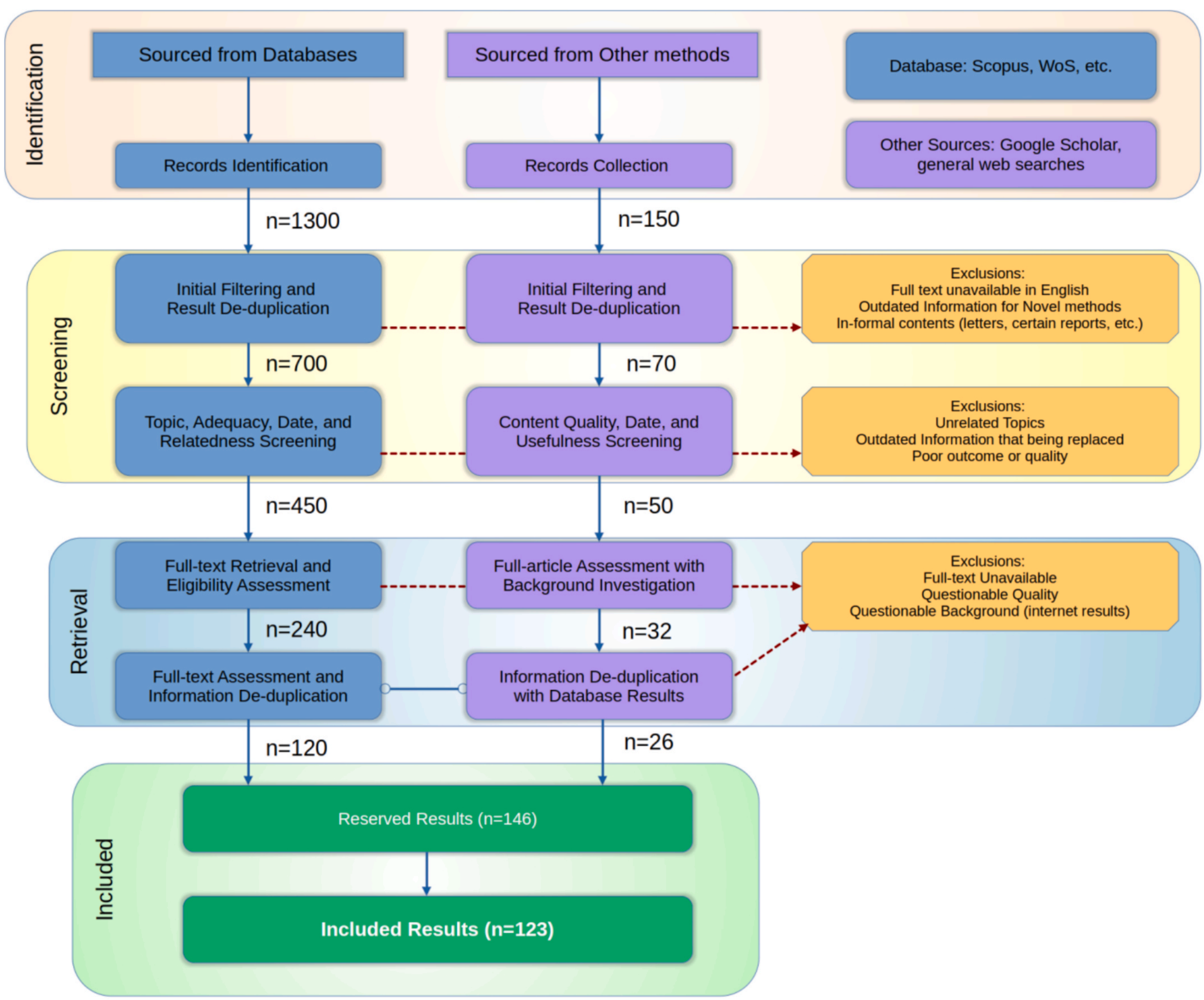


**Fig. 1.** Flowchart of the article and content selection process in the review.

data, and generates measurement outcomes related to cardiovascular conditions and vital signs. This study presents a systematic literature review on non-invasive cardiovascular and vital signs monitoring techniques, conducted in accordance with Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure transparency and reproducibility. The review comprised three main steps. First, the scope was defined to focus primarily on contactless and non-invasive methods, while also considering relevant contact-based techniques for context. Second, the identified methods were reviewed, with their advantages, limitations, and performance compared across multiple dimensions. Finally, the review highlighted key challenges, emerging opportunities, and potential directions for future improvements.

Fig. 1 provides a flowchart overview of how the articles and contents are being selected. Most of the included studies were indexed in major databases, such as Scopus and Web of Science (WoS), using a set of relevant keywords (e.g., contactless, cardiovascular monitoring, non-invasive, radar, ECG, wearable). Additional searches were conducted in Google Scholar and through general web searches to broaden coverage. The initial search retrieved more than 1300 results from databases, and more than 150 results from additional methods, which were then deduplicated and filtered according to predefined conditions to exclude any unsuitable results. Recent publications were prioritised to capture state-of-the-art and emerging technologies, while non-English articles and sources from unverifiable outlets were excluded. A total of 500 articles were being processed in the retrieval process for full text. With further screening being applied to the title, abstract, full-text, and removing articles with unavailable full-texts, a total of 272 articles were retained for detailed assessment of quality, relevance, and compatibility. This detailed assessment results in a total of 146 articles being reserved as candidates. Ultimately, 123 articles were included and reviewed in this study.

Table 1 provides an overview of current cardiac measurement and diagnostic approaches, including both traditional methods and emerging innovations such as wearable devices and contactless methods. It compares several key aspects, including operational constraints (such as working distance and required conditions), invasiveness (contact requirements, potential risks, and time consumption), underlying mechanisms (detection signs and working principles), and key performance metrics (susceptibility to interference, accuracy, and diagnostic value). The table lists the constraints (working distance and special conditions), invasiveness (contact requirements, harm, and time consumption), mechanisms (signs of detection and working principle), as well as key performance (susceptibility to interference, accuracy and diagnosis value). The table is based on the authors' own analysis and synthesis of the reviewed literature and existing technologies, with references included in the corresponding cells.

The article is organised as follows: Section 3 provides a brief overview of traditional cardiovascular monitoring methods, while Section 4 critically reviews emerging contactless and distraction-free techniques. Section 5 discusses key challenges, opportunities, and potential future directions, and Section 6 presents the conclusions.

## 3. Classic techniques

The most commonly used methods for medical screening and diagnosis of heart conditions include PCG, PPG, ECG, and blood pressure measurements. These techniques offer valuable diagnostic information while maintaining a relatively straightforward and accessible approach, making them highly effective for routine use in clinical settings. Classic methods are reviewed in this article because they serve as widely accepted ground-truth approaches in medical areas. Furthermore, the principles behind these techniques form the foundation for many newer approaches, which often build on and extend these established approaches.

### 3.1. Heart auscultation and phonocardiogram

Heart auscultation is one of the oldest and most widely used methods for cardiac diagnosis [11], where heart sounds are auscultated in order to assess the heart's mechanical condition. Through this approach, clinicians can identify cardiac murmurs, abnormal heart sounds, and certain arrhythmias. PCG operates on a similarly straightforward principle, capturing cardiac acoustic signals using a microphone or acoustic sensor. These signals are then visualised as waveforms or spectrograms for analysis. While PCG is closely related to traditional heart auscultation, it offers a more precise and detailed evaluation of the heart's acoustics.

### 3.2. Photoplethysmogram

PPG is a non-invasive method for monitoring heart rate and blood oximetry from the skin surface [12]. It is widely used in both consumer smart devices and professional medical equipment. As shown in Fig. 2, it operates through absorbance-based measurements to generate a pulse wave. Advanced PPG sensors typically use two light sources, most commonly red and infrared (IR) light. These light sources flash back-to-back at the sampling frequency while a photodiode simultaneously detects the residual light. The photodiode's output is inversely proportional to the absorbance and pulse wave intensity. This signal is then conditioned, amplified, and synchronised with the light pulses. During each sampling period, two intensity values —one from red light and one from IR —are captured, allowing the construction of an absorbance graph from the data stream. The PPG controller processes these two traces, utilising spare samples for ambient light cancellation, filtering, and signal processing. From the processed PPG data, algorithms can then calculate key metrics such as SpO2 (blood oxygen saturation) and heart rate.

### 3.3. Electrocardiogram

Among all cardiac measurement and diagnostic methods, ECG is one of the most critical tools for assessing heart functions, and it is widely used for clinical interpretation [25]. It measures the heart's electrical signals as projected onto the body's surface, known as the body-surface EMF. Fig. 3 illustrates the basic working principle of an ECG lead. Contact electrodes placed on the body surface detect these electrical signals and transmit them to an instrumentation amplifier with high input impedance. The amplifier captures the differential voltage, amplifies it, and passes the signal through analogue filtering circuits before it is sampled and acquired as digital data. Once the ECG signal is digitised, it typically undergoes further digital signal processing for additional filtering and to calculate specific cardiac parameters.

ECG signals are inherently weak and highly susceptible to interference [26,27], such as mains power line noise or static discharges. To prevent the instrumentation amplifier from being overwhelmed by these interferences and drifts, a right-leg drive circuit is often used to inject a reversed common-mode offset voltage, maintaining control over the input swings of the amplifier [28]. Depending on the design, the mains power line notch filter can be implemented either in the analogue or digital domain. In multi-lead professional ECG systems, multiple instrumentation amplifiers and acquisition channels are employed. These systems use the standard 12-lead electrode configuration and capture waveforms concurrently. For a typical 12-lead ECG setup, around 8 to 9 acquisition channels are used, where leads like Lead I and Lead II are measured directly, and other leads such as Lead III to Lead aVF are derived using formulas. The precordial leads (V1–V6) can be measured either by calculating the voltage difference between the precordial electrodes and a buffered virtual ground point or by deriving the difference between the precordial and limb lead electrodes.

ECG offers a comprehensive diagnostic framework, allowing clinicians to identify a wide range of cardiac conditions by analysing the

**Table 1**
A summary of current cardiac measurement and diagnosis methods.

| | Technique | WorkingDistance | Special Condition | Harm | Time Consumption | Signs of Detection | Working Principle | Interference | Accuracy | Diagnosis-Value |
|---|---|---|---|---|---|---|---|---|---|---|
| Mechanical Methods | Heart Auscultation, Phonocardiogram (PCG) | Skin Contact | – | – | Short | Cardiac Phonography | Acoustical pickup [10,11] | Med-High | Low | Low |
| | Photoplethysmogram (PPG) | Skin Contact | – | – | Short | Pulse Wave | Optical Absorption [12] | High | Low-Med [13] | Very Low |
| | Common Blood Pressure | Skin Contact, Mechanical-Pressure | – | – | Short | Blood Pressure Waves | Pressurization of SensorObtaining Reaction Plot | Med-High | Medium | Low |
| | Ambulatory blood pressure (ABP) | Contact, Invasive-Sensor | Injection of Sensor | Invasive Monitoring | Long | Artery Blood Pressure | Pressure Sensor | Low | High | Medium |
| | Seismocardiography (SCG) | Contact | – | – | Short | Cardiac Vibrography | Accelerometer [14,15] | Medium | Medium | Low |
| | Ballistocardiography (BCG) | No Skin Contact, Requires Mechanical Pressure | Sitting Still / Lying | – | Short | BallistoCardioGraphyVibrations caused by aorta | Pressure Sensor, Micromovement Pickup, Amplification [16,17] | Very High | Low-Med | Low |
| | Radar-based(Cardiac Baseband) | 5 cm ~ 150 cm | – | – | Long | Body Surface-Cardiac Mechanical Movements | Doppler Radar, Baseband estimation (Long Spectrum) [18] | High | Low-Med | Low |
| | Radar-based(Cardiac Wideband) | 5 cm ~ 150 cm | – | – | Short | Body Surface-Cardiac Mechanical Movements, Vibrography, Phonogram | Doppler Radar, Demodulation, Signal Extraction and Processing [19] | Medium | Med-High | Med |
| Electrical Methods | Electrocardiogram (ECG) | Skin Contact, Electrical | – | – | Short | Cardiac Electrical Activity | Body Surface Electromotive force (EMF)Caused by Cardiac Muscle Activities | Low-Medium | Med-High | Med-High |
| | Contactless ECG | <5 cm | – | – | Short | Capacitively-Coupled Body-Surface Electrical Activity | High Impedance Capacitive-Coupled Sensor, Amplification | Very High | Low-Med | Med |
| | Impedance cardiography (ICG) | Skin Contact, Electrical | – | – | Short | Cardiac Volumetric Change | HF Current Injection Impedance Estimation [20,21] | Medium | Medium | Low |
| | MagnetoCardioGram (MCG) | <20 cm | Usually ElectroMagnetically Shielded | – | Medium-Long | Localized EMFs | Magnetic Field generated by Cardiac EMFs [22] | Med-High | Med-High | High [22,23] |
| Imaging Methods | Echocardiogram (Ultrasound) | Skin Contact, Acoustic-Coupling | – | Occupational harm to operator. [24] | Short-Medium | Cardiac Echography Imaging | Ultrasonic Echography | Med-High | Med-High | High |
| | Magnetic resonance imaging (MRI) | <0.5 m | Strong magnetic field | Pacemakers; Metal Objects; Radiofrequency Burns | Long | Cardiac MRI Imaging | Nucleo Magnetic-Resonance Imaging | Low | High | High |
| | CT | <0.5 m | X-Ray, Highly specialised Professional Device | Ionising Radiation | Short | Cardiac Radiological Imaging | Tomography,3D X-Ray Imaging Reconstruction | Low | High | High |

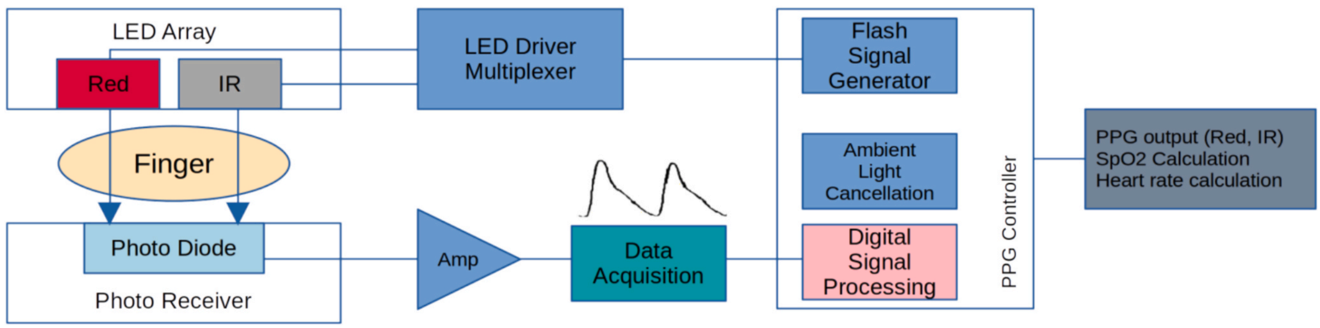


**Fig. 2.** Working principle diagram of a PPG sensor system.

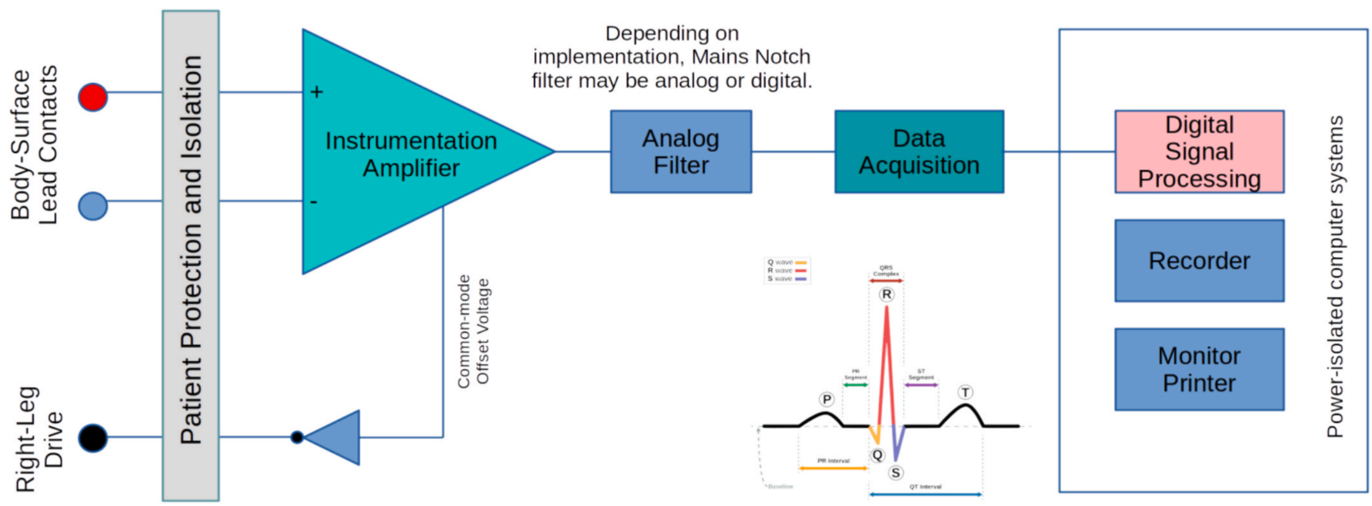


**Fig. 3.** Simplified working principle diagram of ECG System (1 Lead).

heart's electrical activity [25]. It is particularly useful for diagnosing cardiac arrhythmias, heart attacks, conduction system abnormalities, and more. Each condition is associated with specific ECG waveform signatures and measurement ranges. For example, ST segment deviations are indicative of heart attacks, while abnormal PR intervals or QRS complexes suggest conduction system disorders or arrhythmias. Advances in computing technology have enabled automated ECG measurements and analysis, allowing certain abnormalities to be flagged by software. However, the final diagnosis remains the responsibility of a cardiologist, as computer-aided systems often fall short in complex cases where human expertise provides superior diagnostic accuracy. To better assist human-interpretation of the ECG, certain interaction models have been developed to reduce cognitive load and improve the overall accuracies of the ECG interpreters [29].

Although ECG is considered a gold standard in cardiac diagnosis, it is not the sole method for evaluating heart functions. This is because ECG only measures the electrical activity of the heart, limiting its scope. The cardiovascular and circulatory systems are complex, comprising electrical pacemaker systems, conduction pathways, muscular function, and mechanical components. Abnormalities in the heart's mechanical system, structural issues, or problems in the surrounding blood vessels can be difficult, if not impossible, to detect through ECG alone. This is where cardiac imaging techniques come into play, offering a more comprehensive view of the heart's structure and function.

### *3.4. Imaging methods*

These methods are usually considered diagnosis approaches, not for monitoring. The most widely used cardiac imaging technique is ultrasound, commonly referred to as an echocardiogram. This method uses an array of transmitted ultrasound waves and captures their reflections to create detailed images of the heart [30]. Advanced ultrasound techniques, such as Doppler imaging, are often employed to provide additional insights, such as blood flow velocity. An echocardiogram produces real-time video of specific areas of the heart, allowing visualisation and diagnosis of mechanical and structural abnormalities, such as heart failure, atrial septal defects (ASD), ventricular septal defects (VSD), and valve disorders. It can also estimate cardiac performance metrics, such as stroke volume. Like ECG, echocardiography is minimally invasive, requiring only access to the chest area. However, it is more labour-intensive because obtaining clear images requires precise positioning of the ultrasound probe at specific angles between the ribs. The probe must be frequently adjusted, and the operator must simultaneously manipulate the console to achieve a comprehensive view of the heart [31]. This process often takes longer than an ECG, causes more patient discomfort due to required body positioning and constant probe movement, and is impractical for continuous monitoring due to the complexity of the setup. Moreover, over the years, a high proportion of sonographers suffered from repetitive shoulder injuries [24] and have been out of work for a long time or left the profession. One of the key limitations of echocardiography is its relatively low image resolution [32]. Cardiac structures can be difficult to discern, making it unsuitable for diagnosing detailed conditions such as coronary artery disease. Additionally, operating an echocardiogram is a highly specialised skill, requiring extensive training for accurate diagnosis. The quality of the imaging and the precision of the diagnosis largely depend on the expertise of the sonographers.

The disadvantages of the above-mentioned echocardiogram are compensated by advanced and aggressive imaging methods such as CT (Computed Tomography) and MRI (Magnetic Resonance Imaging).

Cardiac X-rays and CT scans use continuous X-ray imaging to create detailed 3D views of heart structure, providing far superior image quality. These methods allow for the visualisation of not only cardiac structures but also critical risk factors like blood vessel blockages, plaques, and other abnormalities. Imaging can be further enhanced with the use of contrast agents to perform angiograms, offering a detailed view of coronary blood vessels and detecting hidden issues such as micro-blockages and myocardial bridges.

However, the use of X-ray and CT imaging comes with significant costs. X-rays used in these procedures involve ionising radiation, and cardiac CT scans typically require comparatively higher radiation doses in order to obtain higher image quality of the cardiac system [33]. Additionally, the injection of contrast agents is an invasive procedure, which can pose risks in certain cases. As a result, cardiac X-rays and CT scans are not only labour-intensive and require specialised expertise but also carry potential harm to the patient. Due to these risks, cardiac CT imaging is generally reserved for situations where the potential benefits clearly outweigh the harms, such as in cases of suspected heart attacks or other serious cardiac conditions.

Cardiac MR Imaging (CMR) has been developed to address some of the issues associated with cardiac X-ray and CT imaging, offering dynamic imaging of the heart through MRI technology. CMR provides a more comprehensive view of cardiac tissues by utilising different MRI sequences and imaging configurations, allowing not only the visualisation of the heart's mechanical structures but also the detection of issues such as myocardial scarring, perfusion defects, and other tissue abnormalities. However, CMR faces its own set of challenges, particularly due to the complexity of MRI and the heart's constant motion. The process is highly time-consuming, as it requires MRI scans with high temporal resolution that must be synchronised with ECG signals to capture images at precise moments in the cardiac cycle. This significantly increases the time required for the procedure, making it difficult to perform on certain patients. Additionally, CMR is still an evolving field with fewer clinical applications compared to more traditional diagnostic methods. The need for specialised equipment and setups makes CMR both labour-intensive and costly, limiting its availability in many hospitals. There are also inherent risks and limitations associated with MRI technology. The strong magnetic fields used during the procedure pose a danger to patients with metal implants, such as pacemakers, making them unsuitable for MRI. Furthermore, the radiofrequency (RF) energy emitted during MRI can, in rare cases, cause tissue burns, adding another layer of risk to the procedure.

## 4. Distraction-Free and contactless techniques

The trade-offs between functionality, safety, and invasiveness in traditional diagnostic methods have driven the development of innovative alternatives. These new methods aim to capture partial measurements that are typically obtained through more invasive or distractive techniques, but in a more distraction free manner. They primarily focus on external mechanical and electrical signals of the heart. Recent advancements have led to the development of several innovative measurement techniques, such as radar-cardiogram [34], ballistocardiogram [35], seismocardiogram (SCG) [15], and contactless ECG. These methods seek to provide valuable diagnostic information while minimising distractions. The working principles and critical evaluation of these techniques are discussed in this section.

### *4.1. Camera-based or optical measurements*

In video-based heartbeat detection, two primary algorithms are commonly used: colour-based detection and micro-movement amplification. The colour-based approach is the most widely adopted, tracking subtle variations from a specific hotspot area of the video to obtain the pulse waveform and measure heart rate [36–38]. This method operates by detecting subtle skin colour changes due to pulse wave-induced expansions in capillary blood vessels. This approach is relatively easy to implement but is highly sensitive to environment and video quality. Light fluctuations, subject movements, camera noises, and video compression can severely affect results. Therefore, its real-world applications are limited, and this approach is primarily used in controlled experiment venues.

Micro-movement amplification focuses on amplifying microscopic skin movements generated by pulses in the arteries. These subtle movements are algorithmically exaggerated to enhance visibility [39]. While micromovement amplification is better suited for detecting vibrations and is somewhat more resilient to lighting changes and colour variations, it demands higher video quality, stable focus, and precise device calibration to achieve accuracy. It is also sensitive to motion artefacts and vibrational noise, which limits its use primarily to specific applications, and respiration monitoring [40], rather than widespread deployment of cardiovascular signs monitoring.

### *4.2. Radar-based approaches*

In comparison to camera-based or optical measurements, radar-based approaches are relatively more reliable and accurate due to their reduced susceptibility to environmental interference. Radar systems utilise various setups and algorithms, leading to considerable variability in accuracy and effective working distance.

#### *4.2.1. Continuous wave (CW) Doppler radar*

Most current radar-based systems employ low-power continuous wave Doppler radar, where the radar front-end emits a constant frequency radio-frequency (RF) wave. As illustrated in Fig. 4, this wave reflects off the chest wall and is down-converted to Doppler shift baseband signals that correspond to chest wall motion. Many studies attempt to estimate heart rate directly without demodulating these signals to achieve seemingly robust results with simple hardware by using methods such as long-window spectrum [41], autocorrelation [42] or time-domain peak-detection [43]. However, these approaches often result in information loss and reduced accuracy, even function failure in certain cases [42]. Their main limitations result from a general lack of beam focus, the presence of null points of un-demodulated, single-channel CW Doppler radar signals [44], and susceptibility to clutter and artefacts. These methods also focus on the fundamental frequency of precordial movements, which can be absent in certain individuals, leading to non-functional results in some experiments. Additionally, methods such as long-window spectrum analysis and autocorrelation can perform less effectively in cases of fluctuating heart rates (e.g., arrhythmias), where the spectral peak distribution becomes wider and is more easily masked by noise and artefacts, particularly in single-channel, un-demodulated CW radar setups.

To address the drawback of direct-detection methods, several demodulation algorithms including Arc-tangent and DACM (Differential and Cross-Multiplication) algorithms, as well as radar front-end architectures (e.g., heterodyne digital quadrature demodulation [45], frequency-tracking radars [46]) were introduced to enhance signal quality and robustness against suboptimal environments. The Arc-tangent demodulation algorithm, recognised as the most popular demodulation technique among CW quadrature radars, is widely utilised because of its generic stability [47] and low computational overhead. DACM focuses on further reducing distortion in the demodulation process and is primarily used for high-fidelity vibrational detection [48]. These algorithms eliminate null points and enable operation over a wider range of distances. However, some implementations still face significant challenges. Demodulation of such radar signals requires high precision in data acquisition and sampling rates, as well as an effective heartbeat detection algorithm. Many existing systems struggle with capturing per-beat heart rhythms due to the use of long-running detection windows for higher signal-to-noise ratio, leading to a loss of temporal information. Additionally, many CW implementations suffer from

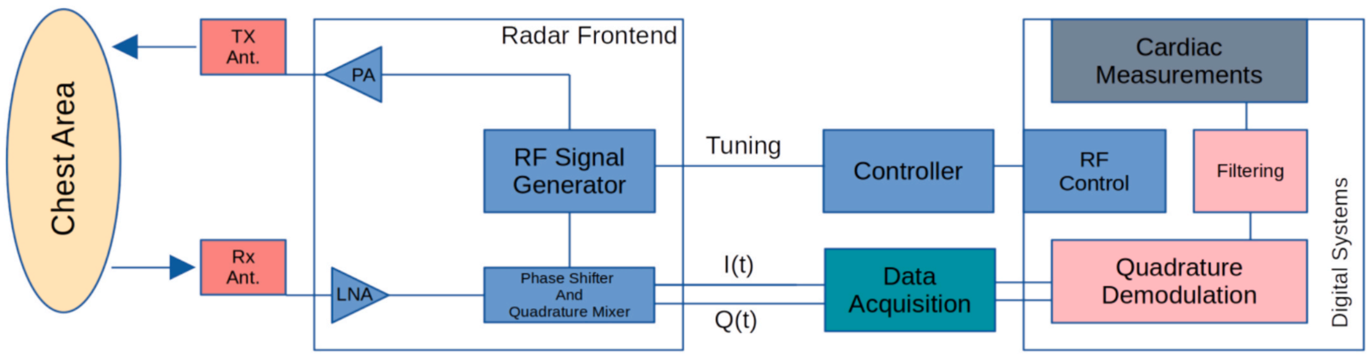


**Fig. 4.** A working principle diagram of quadrature Doppler-radar based cardiac monitoring systems.

limited effective signal bandwidth due to the sampling rates. This limitation can result in signal degradation due to aliasing and makes them unsuitable for retrieving vibrograph or phonocardiograph information. It is worth noting that frequency-tracking [46] or phase-tracking active radars [49] have been explored as alternative solutions to address the null-point issues in single-channel CW radars. These methods utilise active oscillators and Phase-Locked Loop with active control to retrieve motion information, operating with a single channel architecture and no null points. They have demonstrated the capability to detect respiration and heart rate in experiments. However, these methods involve active control and feedback systems along with active radars, making it more complicated than most quadrature demodulation implementations. The involvement of active control can reduce their stability compared to static and passive approaches under certain conditions.

#### 4.2.2. Frequency modulated continuous wave radars

Some research has utilised Frequency Modulated Continuous Wave (FWCW) radars, which use frequency-modulated RF waves and analyse intermediate frequency (IF) signals to obtain ranging information. FMCW radars often use Fast Fourier Transform (FFT) and phase unwrapping for frequency measurements. They offer the advantage of reduced calibration requirements but come with several challenges.

FMCW radars typically measure ranging information only during a single sweep cycle. The sweep repetition frequency (SRF) and ranging accuracy are often a trade-off. To measure cardiac vibrations accurately, FMCW radars generally require a low SRF of several hundred Hz, sometimes even down to 20 Hz [50], limited by the hardware, in order to preserve ranging accuracy. This restriction greatly limits the effective bandwidth and causes aliasing issues, especially for high-frequency vibrations. The heart vibration spectrum can reach several hundred Hz or even exceed 1 kHz in cases of cardiac murmurs [10,51].

A low effective sampling rate combined with noise and even aliasing usually causes significant deterioration of signal quality in the time domain and the frequency-domain effective bandwidth. Thus heart-rate detection methods for FMCW radars often focus on cardiac baseband signals [52], which sacrifice accuracy and temporal information, even with advanced detection methods [53]. While hardware improvements and complex detection algorithms can somewhat enhance heart-rate measurement accuracy [50], FMCW radar systems still rely on windowed detection methods and cannot detect individual heartbeats.

Moreover, FMCW radars usually operate at very high frequencies (around 76 GHz to 81 GHz) to achieve a legally permissible large bandwidth. These high frequencies can limit penetration through air and clothing, reducing both accuracy and effective range.

#### 4.2.3. Highlights and limitations of Radar-based approaches

To achieve the desired performance and overcome the drawbacks outlined above, a combination of carefully designed hardware with dedicated software algorithms is necessary. Yong et al. (2025) developed a radar-based contactless vital signs monitoring system using a K-Band tunable radar [19]. This system, equipped with a high-performance data acquisition system and advanced signal processing algorithms, demonstrated reliable and accurate performance across a wide range of experiments. It effectively measured respiration and heart rates, while providing vibrograph and phonocardiogram information. However, due to the nature of radar-based systems, which utilise array antennas for beamforming, the working distance was limited to 2.5 m, and the maximum deflection angle was 45 degrees.

Despite recent advancements, radar-based approaches are still not yet a fully complete solution for distraction-free and contactless cardiac monitoring. These systems detect minor movements and vibrations from a distance, possessing the following limitations. Firstly, these techniques primarily capture precordial mechanical signs. Without complementary measurement techniques, the scope of information they provide remains relatively limited. While precordial mechanical signs contain certain valuable features, a lot of other important cardiovascular indicators can only be obtained with an electrocardiogram. Secondly, similar to other distraction-free or contactless methods, radar-based systems are vulnerable to both human and environmental factors, where complicated algorithms are usually required to mitigate the effects of motion artefacts [18]. The accuracy of measurements depends on maintaining proper positioning [54] and minimising movement to ensure the radar beam is directed at the chest area. Significant shifts or changes in position can disrupt the radar beam's focus, resulting in inaccurate data. Thirdly, there is currently no established set of standards for radar-based cardiac measurements, including those for heart rate and other parameters, which limits their broader adoption in medical and healthcare settings. To fully realise and further enhance the value of these systems, coordination with other sensor technologies and algorithms is essential.

### 4.3. Contactless ECG-based approaches

Contactless ECG monitoring is not an entirely new concept and has been explored over the past two decades as an innovative method for reducing the distractions and constraints of traditional ECG monitoring. While it has been proven that recognisable ECG waveforms can be obtained through contactless methods, this approach has not yet become practical for professional medical use or general health monitoring. This is primarily due to significant challenges related to signal uncertainty and waveform integrity.

Popular implementations of contactless ECG monitoring often involve embedded electrodes in seat backs, bed mats, or even toilet seats [55], where the body's surface ECG electromotive force (EMF) is picked up capacitively, either by electrodes made with special materials [56], or with common PCBs but with a specifically designed amplifier [57]. However, these methods introduce considerable uncertainty, as the captured waveforms are prone to severe distortion caused by body movements, vibrations, and environmental factors. Additionally, the varying distance between the body and the electrodes acts as a high-pass capacitive filter, which continually shifts the waveform, further complicating accurate signal acquisition.

Waveform integrity is a critical issue that limits the adoption of contactless ECG as a reliable monitoring and diagnostic tool. Traditional ECG systems, particularly the 12-lead standard, are highly dependent on precise electrode placement [58–60], with each lead representing a specific angle in the vectorised cardiac space and playing a crucial role in diagnosis [61]. Diagnostic criteria are largely based on the waveforms observed on these leads, making accurate electrode placement essential—a task that typically requires medical professionals. Misplaced electrodes, depending on severity, can result in a range of diagnosis issues, ranging from artefacts and waveform shifts that severely impact diagnostic accuracy to even causing misdiagnosis [62]. In contrast, contactless ECG methods struggle with arbitrary and shifted electrode placement, leading to ECG waveforms that do not align with standard lead axes. As a result, these methods fail to provide diagnostic value based on current ECG criteria. The only reliable metric that can be consistently obtained from contactless ECG is heart rate, which can be measured by detecting the QRS complex. This limitation is a significant reason why contactless ECG approaches have not gained a strong foothold in the market, as more reliable, cost-effective, and easier methods are already available for heart rate measurement.

One intriguing approach introduced by [63] uses Doppler radar to achieve contactless ECG monitoring. This research takes a distinctly different path compared to other studies in the field. However, the true value of this approach, particularly in relation to ECG monitoring, remains highly uncertain and questionable. The method relies entirely on generative and synthetic techniques to construct the ECG waveform from the mechanical signals detected by the Doppler radar, utilising an AI model trained on existing datasets. While the experimental results produced waveforms that appeared visually comparable to actual ECG waveforms, the synthesised output from the AI model lacks genuine clinical significance. This is because the generated waveform does not originate from any actual cardiac electrical activity. Consequently, this approach is likely to expose its fundamental flaw when applied to samples that deviate significantly from the training data, leading to inaccurate results. The trained model is also prone to overfitting and poor generalisation, as the relationship between mechanical wave inputs and synthesised electrical activity outputs is not inherently valid. This limitation results in its impracticality for realistic ECG monitoring, reducing it to a technique akin to radar-based heart rate monitoring rather than a viable method for comprehensive ECG analysis.

### 4.4. Magnetocardiogram

A recently developed method worth highlighting is the magnetocardiogram (MCG), which detects the weak magnetic fields generated by cardiac electrical activity. During cardiac action potentials, changes in the cardiac electromotive force (EMF) create vectors observable in ECG. These same currents also generate extremely weak magnetic fields, which MCG is designed to measure. MCG uses highly sensitive magnetic sensors positioned near the cardiac region to capture these fields, acquiring signals through one or more channels and processing them accordingly. The resulting waveforms are highly similar to ECG and share many standard features, including the P wave, QRS complex, T wave, and diagnostic markers such as ST-segment elevation or depression. Because MCG captures the magnetic field of the cardiac EMF, its waveforms along certain vector orientations correspond closely to ECG leads with similar orientations. A key advantage of MCG is its ability to provide localised and focused measurements, whereas ECG signals often represent a superposition of multiple EMF vectors. This makes MCG particularly promising in detecting tissue pathologies such as scar tissue, identifying arrhythmia foci, and assessing myocardial ischemia [23]. Furthermore, multi-channel MCG enables magnetic source imaging, which can improve the spatial localisation of the underlying current sources [22].

MCG was first conceptualised in the 1960s, but several factors have limited its adoption. The magnetic fields generated by the heart are extremely weak, typically in the pico-tesla (pT) range [22], necessitating the use of highly sensitive sensors such as tunnel magnetoresistance (TMR) sensors [64], superconducting quantum interference devices (SQUIDs) [65], and optically pumped magnetometers (OPMs) [66]. Moreover, the signals are easily corrupted by background magnetic noise from natural, electrical, and infrastructural sources, as well as from the MCG system itself. As a result, heavy shielding, sophisticated filtering, and averaging techniques are often required to obtain usable waveforms [67]. These technical challenges, combined with the high cost of equipment and operation, currently limit the use of MCG to specialised cardiology laboratories. Consequently, it has not yet been widely adopted in general hospitals, portable healthcare electronic systems, or wearable devices.

### 4.5. Wearable devices

Thanks to advancements in microelectronics and embedded processors, wearable smart devices – particularly smartwatches – have seen widespread adoption in recent years. Many of today's smartwatches are equipped with PPG sensors for heart rate monitoring and, in some cases, SpO2 measurement. These devices are popular because they offer a convenient, minimally distracting way to automatically monitor heart rate while also providing the additional functions of a mobile device.

For consumers, these smartwatches maintain a good balance between user experience and reliability, delivering reasonably accurate measurements with minimal intrusion. However, they are not designed to achieve the highest levels of accuracy, measurement depth, or true non-invasive and distract-free monitoring. Their readings are usually not approved for medical diagnosis, as large artefacts can frequently occur, sometimes accounting for up to half of the signal [13]. Additionally, their use is limited in situations where smart devices are prohibited or where patients are unable to wear them due to physical limitations. Some users also find wearing smartwatches uncomfortable or disruptive to their daily lives, viewing them as more of an interference than a benefit.

With the advancement of artificial intelligence, the value of wearable devices is further explored. Recent studies aim to expand the functionality and values of the specialised wearable devices designed for health monitoring applications. Simultaneous access to multiple types of sensor data gives them a significant advantage as they can perform more advanced algorithms to obtain more in-depth measurements [68]. For example, some specialised smart devices can provide blood pressure measurement by using data from pulse waveform [69], limb ballistocardiogram [70], or even embedded micro radars watches (such as product like RadarPulse, which utilises micro radars to capture pulse waveforms). Along with specialised algorithms and AI, these devices can provide more comprehensive insights into cardiovascular health than traditional wearables. However, despite their enhanced capabilities, these devices are not yet suitable for medical diagnostic applications, as they still face similar limitations and reliability issues as traditional smartwatches. Consequently, their application remains largely in the research and experimental stages.

Another emerging branch of wearable devices is skin-patch or in-body devices. These devices are usually very small and can be fitted to flexible materials, such as adhesion tape base, which holds the electrodes and allows them to be affixed to the body [71], often in the precordial area [20]. Unlike smartwatches, these devices mainly focus on innovative material [72] and circuitry design [73]. They are usually equipped with simple data-acquisition systems and designed to consume very low power [74], which allows them to be powered by a micro battery for extended periods. In order to retrieve recorded data, they usually would require removing from the body, or through some near-field communication approaches. Due to their tape-based design, they require regular replacements, either of the electrodes or the whole sensor, further increasing cost and operation complexity. These methods are not yet widely applied in medical diagnosis, as they generally provide less information than traditional contact-based wearable devices (e.g., continuous ECG and blood pressure monitoring).

### 4.6. Ballistocardiography

Unlike other popular cardiovascular monitoring techniques, ballistocardiography monitors cardiovascular activity indirectly by detecting the ballistic forces generated by the pulse wave as it travels through the aorta [75]. When the heart contracts, it pushes blood into the aorta, the body's largest blood vessel, creating a pulse wave. This wave travels from the ascending aorta, passes through the aortic arch, and reaches the descending aorta. The momentum of the blood generates a force opposite to the pulse wave's direction of travel, which is the signal measured in BCG.

Fig. 5 illustrates the simplified working principle of BCG systems, which typically use specialised weighing scales or weight sensors with amplifying circuits to capture the signal. The resulting time-domain waveform can then be used to service several key cardiovascular metrics, often with the help of ECG or other reference signals [21].

Although BCG is not yet widely used in medical practice, primarily due to its susceptibility to movement artefacts and noise, some studies highlight its potential applications. These include generic heartbeat detector [76], low-cost telemedicine [34], cuffless blood pressure measurement [70], and cardiac output estimation [21], which could be valuable in certain clinical scenarios.

## 5. Key values, challenges and emerging opportunities

While the distraction-free and contactless measurement techniques discussed above have limitations in flexibility, accuracy, and reliability, many still offer valuable direct or indirect cardiovascular insights. Fig. 6 provides a summary of current cardiovascular monitoring and measurement techniques, evaluating them based on distractions, accuracy, and overall value. A clear trend emerges, suggesting that accuracy and value are generally correlated with the level of distractions. However, there are notable exceptions where less distracting methods offer surprisingly high value or accuracy. Cardiological vibrograph information (including SCG and PCG), electrocardiography, and BCG stand out as key areas of interest due to their potential to deliver crucial cardiovascular data with minimal intrusion on the user experience.

The techniques' advantages are further rated in eight perspectives, including application width, time efficiency, reliability, distraction free, harmlessness, bandwidth, information value and working distance. Each technique is evaluated across eight perspectives, with scores ranging from 0 (worst) to 10 (best). Scores are assigned by comparing a technique's performance in each perspective against the optimal performance for that measurement sign and the commonly recognised standard. For example, the "*time consumption*" dimension is assessed relative to the typical expectation of a heart rate measurement, which is only a few seconds. If a method requires five minutes to obtain a reading, it will receive a very low score (0). In contrast, if it provides per-beat heart rate measurements in real time, it will receive a very high score (10). Intermediate scores are determined using the same criteria, with performance mapped linearly between 0 and 10.

Fig. 7 presents a comparison of each technique's percentage advantages across perspectives, according to the normalised scores. Normalisation to a percentage scale highlights the leading techniques for each perspective. Fig. 8 provides a detailed per-method breakdown across all perspectives, while Fig. 9 offers a normalised, perspective-by-perspective view that clarifies the relative weight of each perspective with respect to the evaluated techniques.

Figs. 7 – 9 indicate that the radar-based approaches and contactless ECG approaches provide the best overall performances. To fully explore these two outstanding methods, detailed discussions can be found below.

### 5.1. Radar-derived seismocardiogram and phonocardiogram

With appropriate hardware configurations and advanced software processing, Doppler radars can provide highly valuable information for cardiovascular vibrography. These radars can effectively parse and extract signals that reveal not only cardiovascular movements but also SCG and PCG.

SCG is a relatively well-researched area [14], and it is often used in wearable technology, where gyroscopes [77] or accelerometers [78] are typically used to capture vibrography data. SCG is often employed to assess cardiac function [16], analyse cardiopulmonary physiological changes [79], examine heart failure [80,81] and evaluate recovery outcomes [82]. When properly applied, it can provide a wealth of valuable information [83]. On the other hand, PCG captures akin data but focuses on higher-frequency and broader-band acoustic signals, making it useful for diagnosing physical cardiac abnormalities such as stenosis [84] and valve issues, as well as a generic cardiac dynamics indicator [85], or even as a way of examining heart failure [86,87]. Another intriguing indicator is the low-frequency precordial movement pattern, which reflects volumetric and pressure changes in the cardiovascular system [88]. Although this sign varies significantly from person to person, it remains valuable when combined with vibrography data and can also be captured through radar measurements.

For radar-based approaches, ensuring fidelity and effective bandwidth of the signal is the key to efficient information extraction. When properly utilised, the mechanical signals in the chest area can provide a wide range of valuable information, such as SCG, PCG, and basic movement patterns, which were usually explored using contact-based

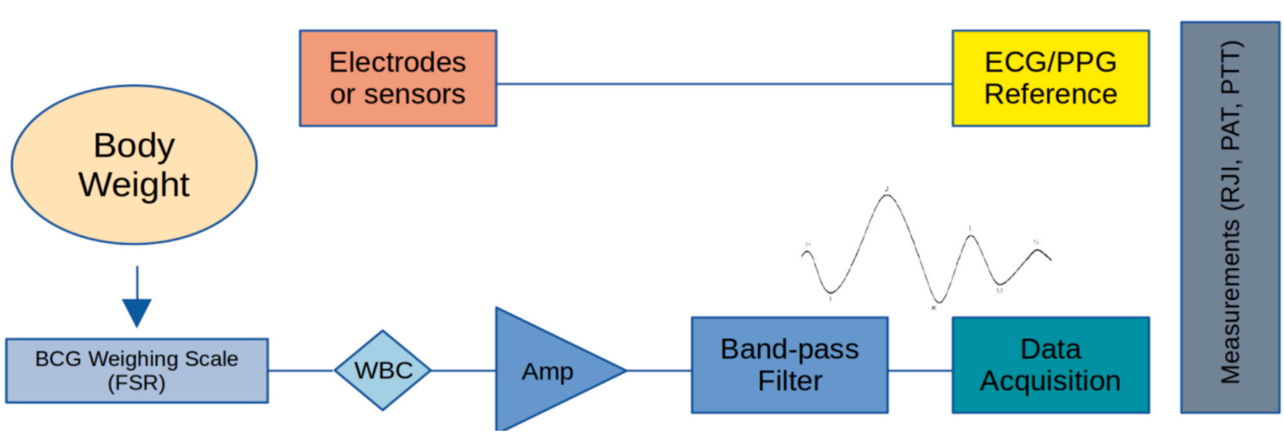


**Fig. 5.** Simplified schematic diagram of a ballistocardiogram measurement system.

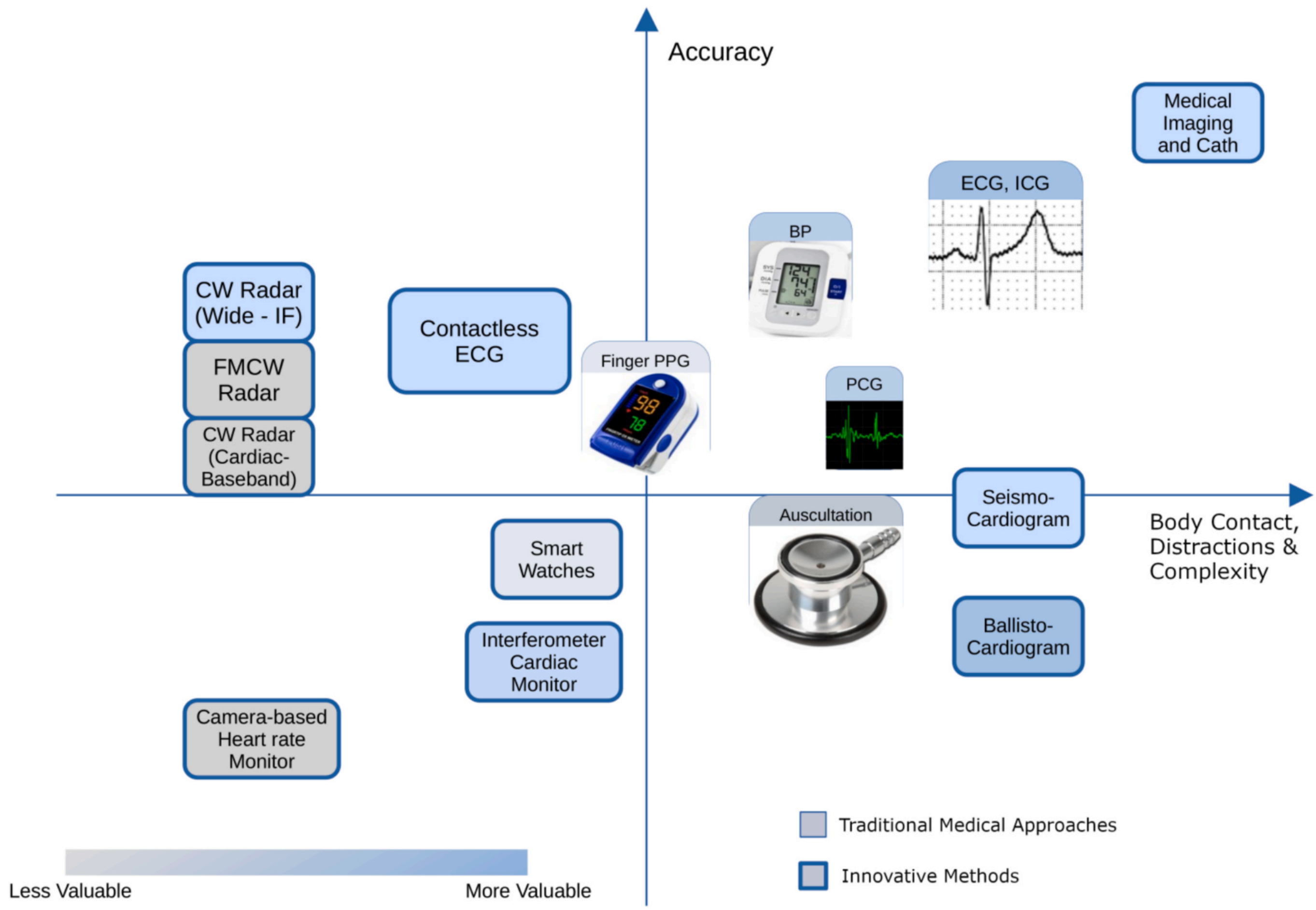


**Fig. 6.** A comparison of current cardiovascular monitoring techniques in terms of invasiveness, accuracy and value.

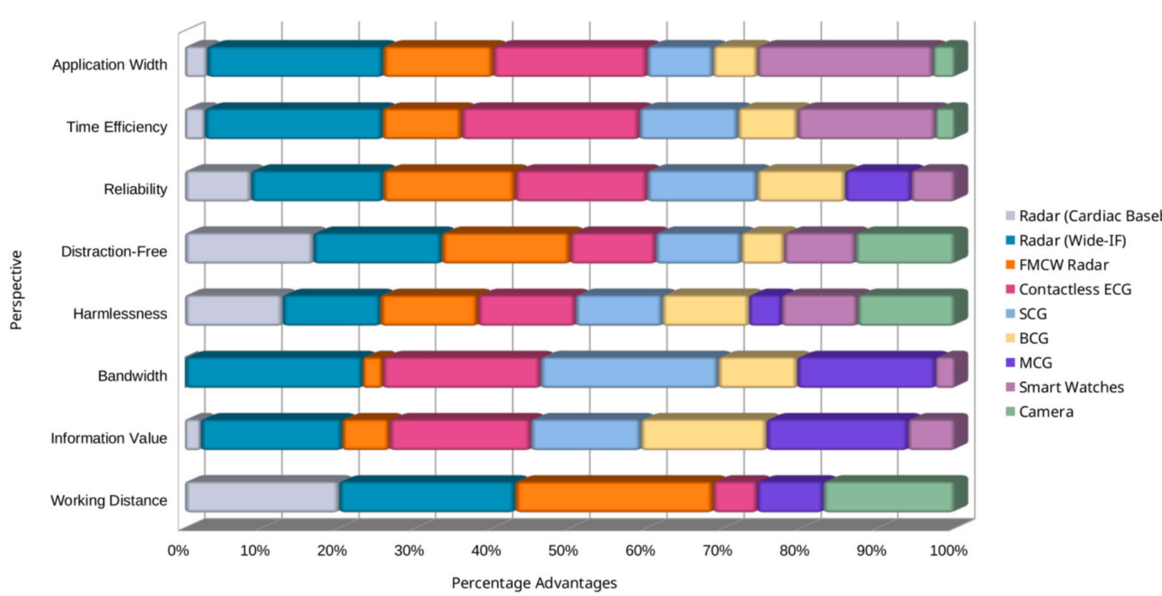


**Fig. 7.** An advantage comparison of the contactless and non-invasive methods with regard to multiple perspectives.

sensors [89]. Radar-based SCG approaches have also been investigated due to its appealing technology [90], as it can provide convenient and timely monitoring of the SCG without the need for special equipment or in a specific environment.

### 5.2. Contactless electrocardiogram

Although concerns regarding signal quality and uncertainty pose significant obstacles to their application, these methods are not without functional value. ECG provides a direct and instantaneous reflection of

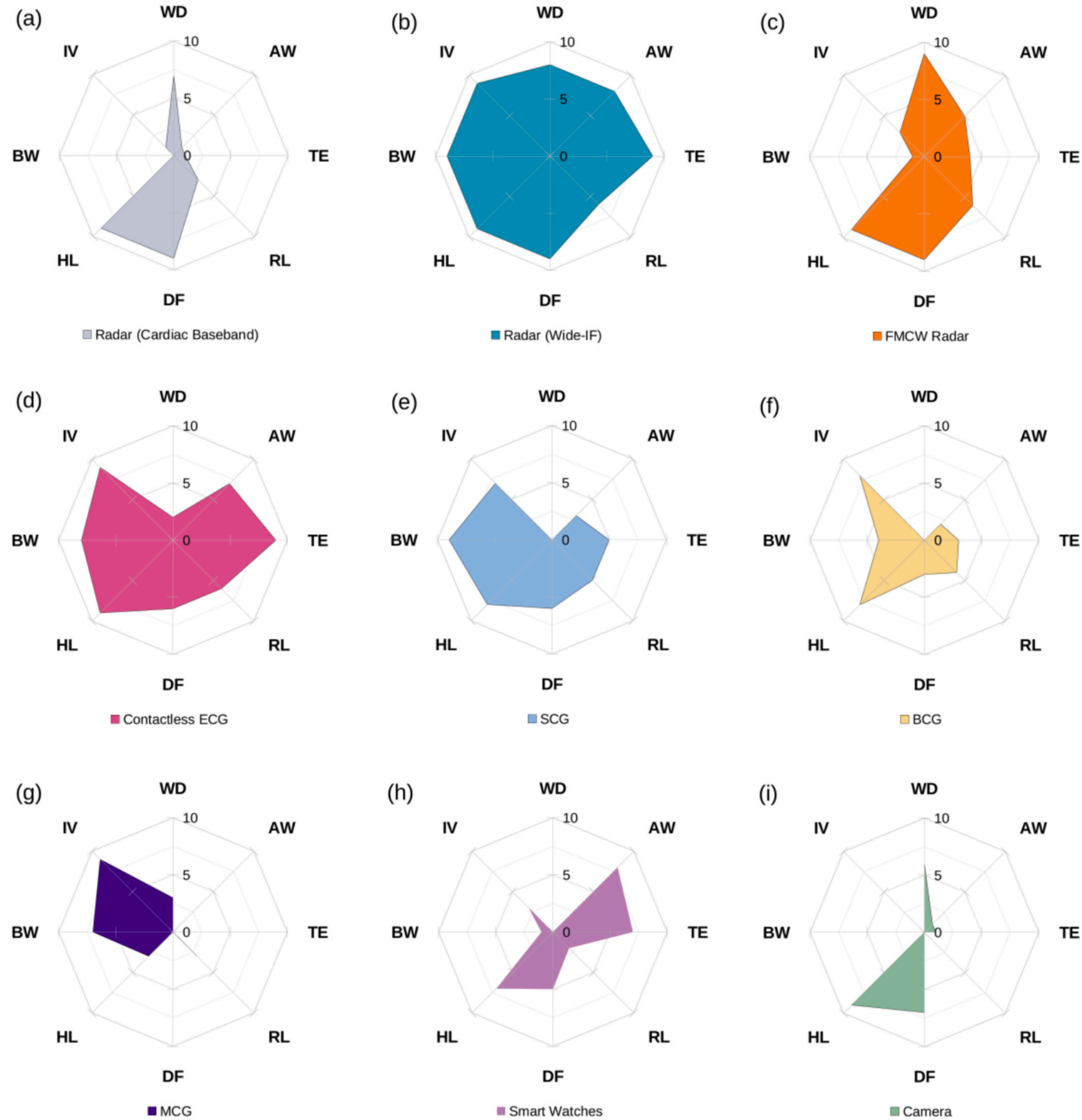


**Fig. 8.** (a)–(i) Comparison of each contactless and non-invasive method with respect to different perspectives. Abbreviations: WD: working distance; IV: information value; BW: bandwidth; HL: harmlessness; DF: distraction-free; RL: reliability; TE: time efficiency; AW: Application Width.

cardiac electrical activity. When combined with other measurements, even distorted ECG waveforms from contactless methods can still offer valuable insights. For instance, they can be used to compare with mechanical cardiovascular signals, facilitating the estimation of movement rates and pulse wave progression. This indirect information can help derive factors such as blood pressure [91], analyse artery health and artery sclerosis [92–95].

Additionally, reconstructing a standard 12-lead ECG from arbitrary lead placements is not entirely out of reach [96], although this aspect has rarely been explored with contactless ECG. With appropriate techniques, it is possible to approximate a standard 12-lead ECG using arbitrarily placed contactless electrodes. Achieving this goal would provide a more comprehensive and valuable insight into the cardiovascular system.

### *5.3. Multimodal measurements and values of conjoining*

Conjoining multimodal measurements and deriving new metrics is a technique that has brought significant benefits to the measurement and analysis process. This approach is widely used in various fields to estimate or measure parameters that are either difficult to measure directly or require distractive methods. A notable example in medical

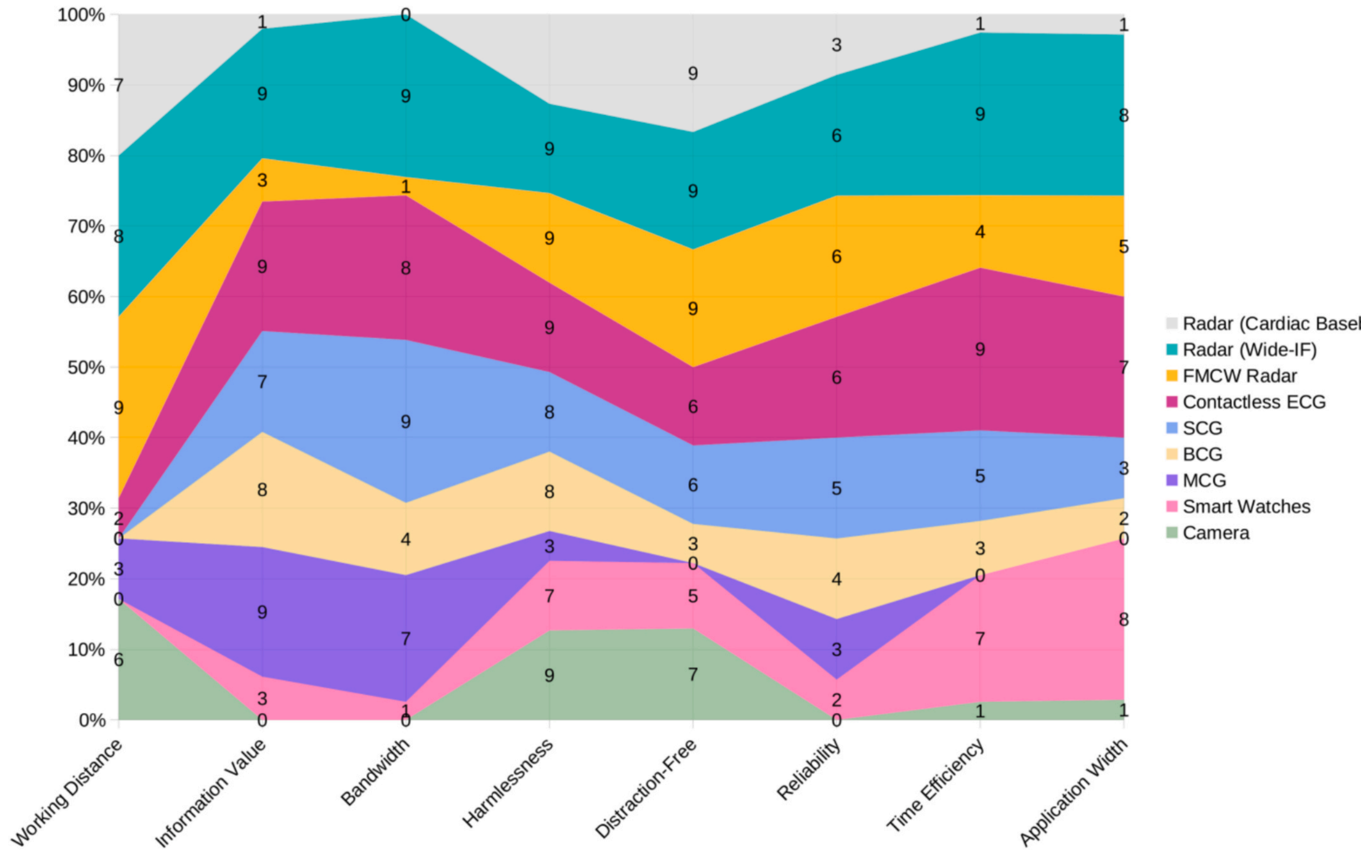


**Fig. 9.** Normalised per-perspective view of each method, showing the individual scores.

applications includes blood SpO2 calculation and cuffless blood pressure measurement [69]. SpO2 is measured by directing light beams of two different wavelengths, typically red and infrared, at the skin. The light that passes through is then captured by a photoelectric sensor, and the measurement of luminance is used to calculate SpO2 levels. Cuffless blood pressure measurement usually involves combining ECG data with pulse wave sensor readings, which measure the pulse transit time and the pulse waveform shape. Blood pressure and arterial stiffness can then be derived based on calculations using these parameters.

Measurements derived from such methods often rely on established physical models, making them relatively accurate and reliable compared to theoretical values. However, some derived measurements, like failure or disease prediction, are based on experience-driven models or statistical methods. In these cases, accurately representing the physical model may be challenging due to the complexity or uncertainty of the entire system. The results from such models are more often probability assessments for specific events within a given timeframe rather than precise measurements of physical parameters.

Both of these measurement techniques currently have limited value in medical monitoring and diagnostics, but careful consideration must be given to their implementation to ensure reliable results. In most cases, physical-model approaches are preferred over experience-based methods when an accurate, theoretically sound measurement is needed. However, developing a new measurement index or applying this approach to certain parameters is not a trivial task. Building a robust physical model can be challenging, especially when there is limited prior research on the topic. In such cases, auxiliary methods and approaches may be necessary to support the model-building process, as discussed in the following section.

### 5.4. *Signal quality and measurement reliability*

Obtaining signals via distraction-free and non-contact methods presents its own set of challenges. Due to the nature of such acquisition, the signals are often highly susceptible to noise and interference. This not only necessitates high-quality hardware for accurate signal capture but also requires sophisticated software techniques to process and extract the desired signals. Proper implementation of these steps is crucial for achieving reliable results.

There are various methods to mitigate signal interference, ranging from traditional approaches from adaptive filtering [97,98], wavelet denoising [99], frequency-domain manipulation [100], and spectrum analysis [101], to more advanced machine learning-based techniques such as deep learning [102], autoencoders [103] and LSTM (Long short-term memory) [104]. However, each method comes with trade-offs, such as loss of signal fidelity, reduced diagnostic value, or increased processing complexity. To preserve signal integrity and minimise distortion, careful attention must be given to both hardware design and software algorithm development. Similar concerns regarding motion-induced artefacts and ambient vibrations have been explored in environmental monitoring domains, such as transport noise and vibration analysis, highlighting the need for robust hardware and advanced filtering strategies [105,106].

### 5.5. *Application of artificial intelligence and its trustworthiness concerns*

The rapid rise of AI has inspired new solutions to a wide range of challenges in this area. AI can assist in modelling core processing in multimodal systems and serve as a validation tool for obtained results. However, it is crucial to use AI responsibly, particularly in fields like measurement and instrumentation, where precision and regulatory compliance are especially critical in medical applications. To ensure that measurements retain their clinical value and significance, strict adherence to guidelines, regulations, and standards is essential. Therefore, the integration of AI into heart monitoring and measurement requires caution and careful oversight.

On the other hand, AI is widely applied across all stages of cardiac monitoring and diagnosis, especially in research and experimental settings. Fig. 10 summarises the utilisation of AI across a wide range of cardiac monitoring and diagnosis methods, highlighting its application across multiple dimensions and stages. In traditional methods, such as contact-based ECG, key areas for AI application include myocardial infarction (MI) detection, arrhythmia identification, and critical events prediction. Multiple different algorithms are selected according to the specific task, ranging from simple multi-layer perceptron[107], to deep neural networks in modern and complex applications. Software platforms like *Queen of Hearts* [108] is often used as an assistive tool for medical professionals. The deep learning model in this platform can detect a range of cardiac occlusions and MI, even in cases without directly observable ECG signs [109,110]. Numerous studies have also focused on AI-driven detection of MI, multiple arrhythmias [111], hypertension-induced critical events [112], and heart failure assessment [113].

Unlike highly directed measurements like ECG, some models detect cardiovascular issues with broader inputs, including mechanical signals such as PCG, SCG, or BCG. AI has been used to predict heart valve disorders solely from PCG data, electronically equivalent to cardiac auscultation, allowing detection even in the absence of audible signs [114]. AI's advanced signal processing capabilities make it well-suited for analysing rougher inputs like PCG and smartwatch-based wrist PPG. Wearable smartwatches have become a major focus for AI-driven cardiac monitoring, thanks to advancements in embedded systems and IoT technologies. These devices primarily use wrist PPG, where AI enhances signal quality, detects arrhythmias, and assesses sleep and stress levels. Due to the computational limitations of wearable devices, some smartwatches rely on cloud-based AI processing, with dedicated apps providing trend analysis of recorded data. However, most AI implementations in these devices remain proprietary and subject to frequent updates, making it difficult to evaluate their accuracy and reliability.

Contactless cardiovascular monitoring is a relatively advanced field, with most approaches focused on measuring or estimating heart rate using various contactless sensors. However, due to the inherent limitations of these methods, such as lower measurement reliability and reduced medical values compared to traditional medical techniques, AI applications in this area are still limited, particularly for evaluation and diagnosis. Nonetheless, AI can help address some of these challenges. Firstly, distraction-free and contactless signals are often noisy and prone to interference, making them challenging to process with traditional methods and filters. In the least reliable contactless heart rate measurement approach, camera-based detection, AI is primarily used for image enhancement, region of interest (ROI) detection [115], and improving heart rate prediction accuracy [116]. In more reliable contactless methods, such as radar-based and contactless ECG systems, specialised AI models [99,100,102,104] have been developed to process these signals more effectively. These models outperform conventional techniques in tasks such as denoising and heartbeat detection. When implemented with appropriate constraints, they can enhance signal quality without significant fidelity loss.

Moreover, AI can play an important role in uncovering relationships and modelling multimodal data analysis [117,118]. Deducing and predicting new measurements from combined multimodal data is inherently complex and often lacks documented formulas or models. AI is able to discover hidden relationships between measurements and target values. By utilising advanced analytical techniques, it can establish these relationships and build accurate predictive models. This technique is also called soft sensors. Moreover, AI can assist in the validation process [119]. Beyond uncovering relationships between available measurements and hypothesised outcomes, AI can demonstrate the clinical significance of new measurements, particularly when direct comparisons with established ground truths are not feasible. In research, novel measurement indexes may be introduced to estimate specific cardiological factors, but traditional methods may lack reference measures for validation. In such cases, AI can help establish connections between these new indexes and established clinical markers, reinforcing their reliability and significance.

However, while AI offers advantages across various domains,

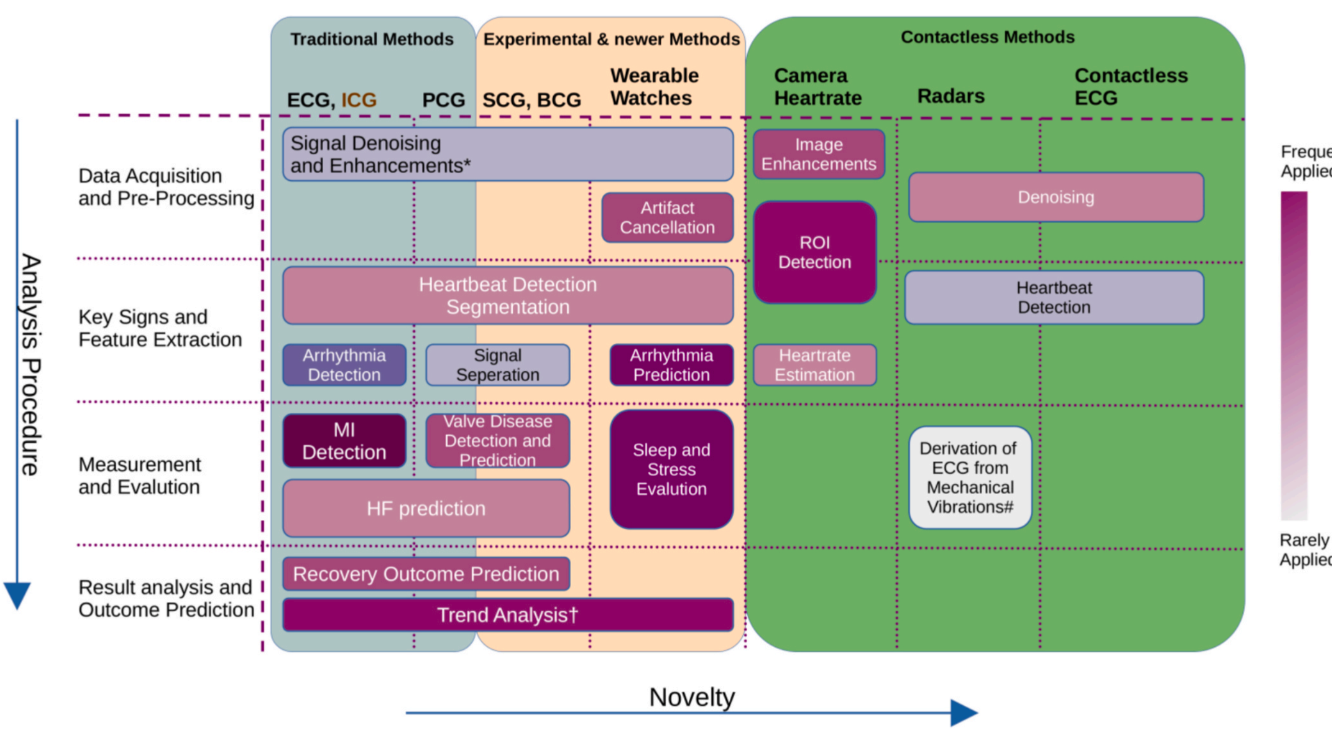


**Fig. 10.** The summarisation of AI application in cardiac monitoring and diagnosis.

concerns about responsibility and trustworthiness arise simultaneously. One major issue is AI's inherent *black-box* nature: its decision-making processes are often opaque and difficult to interpret. Unlike traditional diagnostic methods grounded in well-established physical principles, AI-generated results require careful scrutiny, particularly in medical applications. There have been cases where AI has produced questionable or theoretically implausible results. For example, some models claim to derive ECG waveforms from cardiovascular mechanical waves detected by radar [63]. This approach relies on a generative model, meaning the ECG waveform is synthesised rather than directly linked to the heart's actual electrical activity. As a result, such outputs should be treated with caution when considered for cardiac monitoring or diagnosis. Another critical concern is data security and privacy. Unlike common user data, medical data is considered highly sensitive and must be stored under stringent safety and security standards, as regulated by law. Many cloud-based services and client applications lack proper certification for handling sensitive data, making them vulnerable to breaches. From an ethical and patient confidentiality standpoint, cloud-based and AI-driven solutions are often viewed with scepticism. Patients may be reluctant to accept them due to untransparent workflows, uncontrollable data sharing, and cybersecurity risks [120].

Addressing these problems is far from straightforward, as they require fundamental changes across the entire pipeline and can be resource-intensive. Nevertheless, several strategies may help mitigate these challenges. For AI opacity, reliability, and interpretability, responsible and well-scoped deployment is crucial to improving transparency and trustworthiness. This includes incorporating explainable and rigorously validated AI methods, limiting the scope of AI applications, and refining feature-extraction algorithms rather than feeding under-processed data directly into models. Interpretability strategies should also be developed in parallel with AI methods to ensure seamless integration into existing diagnostic and analytical frameworks. For medical data security and privacy, stronger legislation, layered security mechanisms, and secure data frameworks are essential. Practical measures include implementing end-to-end encryption, restricting the use of proprietary or unverified software in critical systems, incorporating secure data pipelines, and strengthening end-device protection through better privacy hygiene practices [121]. While absolute cybersecurity cannot be achieved, the overall level of protection and effectiveness can be substantially improved by combining regulatory enforcement with advanced security methods, which is an especially crucial consideration in medical applications.

### 5.6. Challenges in regulatory and standardisation

In contrast to many other fields, medical applications are highly regulated due to their direct interaction with humans, associated safety, privacy, and ethical concerns, and the potentially catastrophic consequences of system failures. Before deployment, a medical device must obtain multiple certifications and comply with established standards (e.g., the International Electrotechnical Commission (IEC) 60,601 series for ECG devices), which often vary across countries and organisations.

For newer contactless and non-invasive methods, however, standardisation remains limited. These approaches are mostly experimental, with working principles that differ widely from one another and from traditional methods, leaving few existing standards that can be directly applied. For instance, there are no recognised standards for assessing the accuracy and reliability of radar-based cardiovascular monitoring systems. Existing regulations typically apply only to the radar hardware itself (e.g., transmission frequency and power limitations set by the Federal Communication Commission (FCC)) or to general hardware requirements (e.g., Restriction of Hazardous Substance directive (RoHS) compliance). This lack of standardisation creates significant challenges for certification and clinical deployment. Combined with the fact that most devices are still at the research stage, they are rarely applied directly to disease diagnosis and instead used mainly as assistive tools in clinical trials.

For medical AI components, regulatory frameworks are somewhat more developed (e.g., International Organization for Standardization (ISO) 13485, ISO 14971, IEC 62304), but remain fragmented compared with AI governance in other established fields [122]. Certification is particularly difficult because AI is often considered opaque, whereas medical technologies typically require transparent mechanisms and predictable outcomes. Standards also vary across countries and regions, further complicating the approval process. As a result, certification is often sparse and unsystematic. Only products backed by significant resources and extensive testing, such as smartwatches and certain AI-based ECG diagnostic systems [108], achieve wider certification. Even then, they may face obstacles in jurisdictions where standards are unrecognised or incompatible. At present, medical AI certification is still largely adapted from general software standards, with validation focused mainly on performance rather than dedicated regulatory frameworks.

### 5.7. Validation of monitoring techniques

Existing measurable signs are those that can be assessed using established techniques, such as blood pressure and cardiac stroke volume. These signs are relatively straightforward to verify and validate, as they can be compared directly to known ground truths. This allows for a clear evaluation of accuracy and error rates, though comprehensive statistical steps have to be followed for the reliability of results [123].

In contrast, contactless signs and measurements may lack direct ground-truth counterparts. These signs, derived from multimodal data processing, offer new ways to indicate cardiovascular parameters. In such cases, the validation process focuses on demonstrating the value and significance of these signs in evaluating cardiovascular performance or predicting cardiovascular diseases. AI can be employed to establish relationships between the novel signs and patient conditions, thereby confirming their relevance and accuracy.

### 5.8. Comparative discussion

Cardiovascular monitoring relies on a wide range of methods, each built on different signs and principles. Classical techniques such as PCG, PPG, ECG, and blood pressure measurement are the most commonly used in clinical practice. When greater diagnostic detail is required, imaging methods such as ultrasound, CT, or MRI may be employed, though at the expense of higher cost and longer scan times. These methods are well established, supported by comprehensive diagnostic standards, and valued for their accuracy and reliability. However, they are often invasive, time-consuming, and technically demanding, requiring trained professionals to operate, which limits their use mainly to clinical environments.

In contrast, newer methods aim to improve user experience, ease of use, and broader accessibility by employing non-invasive or contactless sensing. Examples include radar sensors that detect chest wall motion induced by cardiac activity, and contactless ECG and MCG sensors that use capacitive sensing to capture cardiac EMFs without skin contact. Wearable devices, such as smartwatches, offer additional convenience for monitoring parameters like heart rate and $SpO_2$. These approaches reduce user burden and interference with daily life but face trade-offs, including reduced signal quality, limited diagnostic value, and higher susceptibility to noise and artefacts. Furthermore, wearables cannot always be used in specific environments or scenarios.

To address these challenges, multimodal integration offers a promising path forward. While individual non-invasive modalities may provide limited information on their own, combining them can enable more comprehensive analysis, improve artefact detection and cancellation, and reveal features not accessible through a single modality. When further supported by advanced algorithms and carefully applied AI methods, these systems can compensate for signal limitations, improve diagnostic value, and increase reliability.

## 6. Conclusions

This article reviewed, compared, and analysed a wide range of cardiovascular monitoring techniques, with a particular focus on non-invasive and contactless methods. Emerging approaches, such as radar-based sensing of precordial pulsations and vibrations, capacitive ECG, camera-based PPG, as well as comparable non-invasive methods including SCG, BCG, and wearable smartwatches, were examined in terms of their working principles, advantages, and disadvantages across multiple performance dimensions.

While contactless monitoring offers clear benefits, including distraction-free operation, flexibility, and user-friendliness, it still faces inherent challenges in signal quality, reliability, and overall performance. Potential solutions include advanced hardware (e.g., wideband analog CW Doppler radar, contactless ECG), effective signal processing, responsible AI, and multimodal data fusion, which together can mitigate signal degradation and enrich diagnostic information.

With these improvements, contactless cardiovascular monitoring has the potential to complement and, in some cases, surpass traditional methods. By leveraging their strengths while addressing current limitations, these techniques could significantly enhance accessibility and usability, offering transformative opportunities for cardiovascular healthcare across diverse applications.

## Ethics statement

This article does not contain any studies with human participants or animals performed by any of the authors. No Generative AI is used in any part of the article writing.

## CRediT authorship contribution statement

**Qi Yong:** Writing – original draft, Writing – review & editing, Conceptualization, Visualization, Formal analysis, Data curation. **Lichao Yang:** Writing – review & editing, Supervision. **Attila Kardos:** Supervision. **Yifan Zhao:** Writing – review & editing, Supervision.

## 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.

## Data availability

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

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