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Review Paper

Review of Microphone-Based Contactless Vital Signs Monitoring Systems

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Microphones are sensors common to a variety of the Internet of Things (IoT) and healthcare applications. Many examples have proved that microphones can be useful in detecting, e.g., abnormal breathing rates. There are already applications that serve this purpose, e.g., respiratory acoustic monitoring, ResApp, etc. Breath signal was studied using a range of technologies and sensors, including the most common: radar, accelerometer, wearables, and so on. The majority of these sensors are attached to the body of a monitored person. However, the emergence of COVID-19 has drawn particular attention to the importance of using non-contact technologies for monitoring breath signals and other vital signs. This paper presents a comprehensive review of microphone-based non-contact vital sign monitoring, including the methodologies and concepts, while identifying new research gaps and opportunities for the future studies.

Keywords: beamforming; microphone; machine learning; vital signs.

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Acronyms

CIR – channel impulse response,
DOA – direction of arrival
DYCTNN – dynamic convolution-transformer neural network,
FFT – fast Fourier transform,
FMCW – frequency-modulated continuous wave,
FPGA – field-programmable gate array,
IDRes – identity-based respiration monitoring system for digital twins enabled healthcare,
IoT – Internet of Things,
MEMS – microelectromechanical microphone,
NCVS – non-contact vital signs,
RIP – respiratory inductance plethysmography,
RMSE – root-mean-square error,
SNR – signal-to-noise ratio,
STFT – short time Fourier transform,
TDOA – time difference of arrival.

1. Introduction

The vulnerability of today's healthcare system was evident during COVID-19 pandemic, a serious global concern in which the number of patients outweighed available equipment. It was a common practice that the respiratory apparatus, known as ventilators, was shared between two patients (Garzotto *et al.*, 2020). According to (Branson, Rodriquez, 2023; Tsai *et al.*, 2022), the use of ventilators increased by 30 % in case of adults and 15 % in case of children following COVID-19. This indicated that persons with normal breathing problems have been neglected during this period. This group of people includes both the younger and older generations.

The application of digital processing to a microphone signal makes it suitable for various research applications. Microphones, commonly used for recording audio, have now evolved into sophisticated non-contact monitoring sensors. By using advanced signal processing techniques, microphones can be used to sense and analyze vital signs such as heart rate and respiration rate without making contact with the body of the target. This new approach offers numerous advantages over traditional methods, resulting in microphone-based non-contact monitoring systems being a promising technology for remote health monitoring and wellness applications.

A microphone is a transducer that converts sound waves to electrical signals. It detects slight changes in air pressure induced by sound and generates an

electrical signal representing the acoustic sound waveform. This electrical signal can subsequently be amplified, processed, recorded, or transmitted for numerous purposes such as telecommunications, audio recording, active noise control and speech recognition. Microphones vary in kind, design, and technology, but they always work on the principle of converting acoustic energy (sound pressure) into electrical energy. Common types of microphone include dynamic, condenser, ribbon, piezoelectric microphones and microelectromechanical microphone (MEMS); each comes with different properties that make it best suited for different applications.

Numerous studies have been conducted in the area of contact and non-contact vital signal monitoring. Among the research results, a few include thermal imaging cameras (Savazzi *et al.*, 2020), photoplethysmography (PPG) (Ryu *et al.*, 2021; Artemyev *et al.*, 2020; Boccignone *et al.*, 2023; Hashim *et al.*, 2023; Khong, Mariappan, 2019), doppler radar (Islam *et al.*, 2019; Joshi *et al.*, 2023; Edanami *et al.*, 2022; Zhang *et al.*, 2023a; Wahyu *et al.*, 2022; Mercuri *et al.*, 2018), microwave sensors (Katoh *et al.*, 2023; Celik *et al.*, 2011; Dei *et al.*, 2009), and acoustic sensors (Okamoto *et al.*, 2023; Xiao, Yu, 2021; Liu *et al.*, 2022; Jahanshahi *et al.*, 2018; Smithard *et al.*, 2017). Other popular choices are video cameras (Huang *et al.*, 2021; Sabokrou *et al.*, 2021; Artemyev *et al.*, 2020; Hsu *et al.*, 2020; Shokouhmand *et al.*, 2022) and fiber cable (Xu *et al.*, 2020; 2021; Liang *et al.*, 2023; Zhao *et al.*, 2023; Lyu *et al.*, 2022). However, using microphones for non-contact recording offers several advantages, including robustness, the ability to capture detailed information (Kranjec *et al.*, 2014; Fang *et al.*, 2016) and their sensitivity across a wide range of coverage, making them adaptable to different scenarios. Microphones are also useful for making respiratory sounds accessible via phones, laptops, and other portable devices (Massaroni *et al.*, 2021), although this approach has its own drawbacks. This review focuses on microphones for non-contact vital sign monitoring and it is divided into sections discussing various methods that have been developed in this field. These methods include beamforming techniques, smartphone-based solutions, hardware and artificial intelligence (AI) based approaches.

2. Microphone

The advent of the Internet of Things (IoT) has made the use of microphones more relevant, increasing their usefulness by 17 % per year (Beckmann, 2017). This may be a result of microphones changing from just a device for voice reception to their adaptation to mobile applications. Modern applications of microphones include mobile phones and tablets, cameras, wearables, bluetooth speakers, and security cameras. They can act as a sensor for detecting the respiration or heart rate of humans. Different microphones are being used in sound analysis due to their unique capabilities and features (Balgemann *et al.*, 2023). Moreover, some of them are equipped with a digital signal processor that enables them to modify the audio signal based on the distance and direction to the sound source. The pulse-density modulated microphone has been recently gaining attention due to its ability to delivering audio to digital processors, but its high-order decimation filter for pulse code modulation increases the cost and power consumption when used as a beamformer (Ipenza, Masiero, 2018). Table 1 shows a summary of microphone applications found in the literature.

2.1. Types of microphones used in audio signal analysis

2.1.1. Dynamic microphones

Dynamic microphones have the advantage of providing balanced sound recording. They are also durable,

Table 1. Applications of microphones from the literature.

Paper	Microphone type	Placement	Contact/Non-contact
(Doyle, 2019)	Electret	Attached to trachea, lungs	Contact
(Valipour, Abbasi-Kesbi, 2017)	Capacitor	Chest region	Contact
(Kavsaouğlu, Sehirli, 2023)	Stethoscope	Chest region	Contact
(Zhang *et al.*, 2023b)	MEMS	–	Non-contact
(Shih *et al.*, 2019)	Smartphone	Mouth/Chest	Contact
(LoMauro *et al.*, 2022)	–	Chest wall and lungs	–
(Dafna *et al.*, 2015)	Rode NTG-1 directional	–	Non-contact
(Islam *et al.*, 2021)	Wearable and smartphone	Chest region	Contact
(Chauhan *et al.*, 2017)	Smartphone and wearable		Contact
(Khodaie *et al.*, 2021)	MEMS	Mouth region	Contact
(Khatkhate *et al.*, 2022)	Pressure sensors	Ribcage	Contact
(Fang *et al.*, 2023)	Circular microphone array	–	Non-contact
(Xu *et al.*, 2022)	Smartphone	–	Non-contact
(Xie *et al.*, 2020)	–	Modelling of chest region	Contact

portable, and capable of producing high-quality sound. These microphones work on the principle of electromagnetic induction, the movement of a wire in a magnetic field creates an electromotive force (EMF) in the wire, which forces the current to flow. When sound waves hit the diaphragm, it moves either the magnet or the coil, creating a small current that can capture sounds from up to one meter away.

2.1.2. Condenser microphone

This kind of microphone functions as a capacitor consisting of two plates near each other, one of which acts as the diaphragm. When sound reaches the diaphragm, it vibrates, generating changes in capacitance, resulting in an electrical representation of the acoustic signal. Condenser microphones have a standard diaphragm diameter: large and small; the small having the advantage of being more compact and sensitive to picking up higher frequency sound (PreSonus, 2022). Its high fidelity, excellent frequency response, low noise levels, and sensitivity make it appropriate for acoustic research (Todorović *et al.*, 2015).

2.1.3. Electret microphone

An electret microphone is a type of condenser microphone that eliminates the need for a high-voltage power supply by using a permanently charged material called an electret. Like most microphones, it consists of a diaphragm placed near a metal backplate, forming a capacitor. When sound waves impinge on the diaphragm, it vibrates and changes the capacitance, generating an electrical signal corresponding to the sound. They are commonly used in devices such as mobile phones, hearing aids, and voice recorders because they are compact, less expensive, and they require a small power source for their in-built preamplifier (Open Music Lab, 2022).

2.1.4. Microelectromechanical microphone

The MEMS microphone operates by using a tiny mechanical system etched onto a silicon chip to convert sound waves into electrical signals. It is made of a flexible diaphragm and a fixed backplate which forms a variable capacitor. The capacitance of the capacitor changes as sound waves hit the diaphragm, and this change/variation is then converted into an electrical signal by an integrated circuit. MEMS microphones are gradually replacing electret microphones due to their smaller size and greater suitability for smartphones. They have the advantage of picking up signals equally from all directions, making these microphone omnidirectional. They are also tiny in size and consume low amount of power. This implies they can be used to determine the direction of sound in a microphone array (Wang *et al.*, 2020). However, when MEMS microphone recordings are converted to electrical signals, some noise is introduced (Rose, 2022). The audio data used in smartphones is generated digitally as a result of current movement in a very small mechanical sound diaphragm. MEMS microphones are employed in mobile devices because of its tiny footprint and good performance (Picchio *et al.*, 2019).

Table 2. Comparison of non-contact health monitoring technologies.

Technology	Strengths	Weaknesses	Applications	References
Microphone-based	Low cost, high accuracy in detecting physiological sounds, easy integration with existing devices, non-invasive, versatile, low power consumption	Sensitive to noise, privacy concerns, limited range 0.5 m–1 m for breath sounds	Respiratory monitoring, heartbeat detection, speech recognition	Fukuda *et al.*, 2018; Aarts, 2019; Genova, 1997; Sharma *et al.*, 2019
Radar-based	Accurate for motion detection, capable of detecting chest movements for breathing rate monitoring, non-contact, works in the dark	Expensive hardware, limited in detecting internal physiological sounds, consumes more power than other methods, long range between 10 m and 50 m	Breathing rate monitoring, heart rate monitoring, motion detection	Sakamoto, Yamashita, 2019; Zakrzewski, 2015; Lv *et al.*, 2021
Infrared sensors	Effective for detecting body temperature changes, non-contact, can detect presence or absence based on heat signatures, variable power consumption	Requires line-of-sight, affected by ambient temperature variations, limited to surface-level observations, calibration needed, range between 0.1 m to 4 m	Body temperature monitoring, motion detection, sleep studies	Thundat *et al.*, 2000; Fraden, 2014; Yang *et al.*, 2022
Ultrasonic	Good for distance measurement and obstacle detection, non-contact, safe to use, non-invasive, low power consumption	Limited resolution for detecting fine physiological details, requires direct path for sound waves, affected by material properties, range between 0.3 m to over 10 m	Fall detection, obstruction detection, motion monitoring	Hoctor *et al.*, 2008; Barany, 1993; Toa, Whitehead, 2019

2.2. Comparison of non-contact health monitoring technologies

A microphone-based non-contact monitoring system is a better alternative to other non-contact monitoring methods such as radar, infrared and ultrasonic sensor. It is capable of monitoring breath signal, heartbeat detection and identifying vocal patterns. These capabilities are possible due to its ability to leverage on the properties of sound waves to monitor physiological features. Table 2 outlines the advantages and disadvantages of these methods.

2.3. Microphone array

A microphone array (MA) is an arrangement of several microphones positioned to gather signal from different spatial locations. The main goal of MA is a robust representation of the signal. It works on the principle of sound propagation that several inputs are able to either attenuate or enhance by processing signals from specific directions even in the presence of noise (Dey, Ashour, 2018; Levy *et al.*, 2010; Doclo *et al.*, 2015). MAs are essential in non-contact measurement of signals, leveraging on the combined power and sensitivity of the connected microphones. The spatial arrangement of MA consists of several configurations which include linear arrays, circular arrays or spherical arrays, depending on the purpose an array is intended (Alexandridis, Mouchtaris, 2017). The configurations also determine the spacing between the connected microphones (Dey, Ashour, 2018). Exemplary array arrangements are shown in Fig. 1. In this configuration, the microphone may be replaced with a smartphone or a beamforming method. The difference between a single microphone and an array arrangement is that a single microphone cannot provide the direction of a sound source and reduction of reverberation without the need for post-processing. An array arrangement, on the other hand, can improve the speech signal quality using the received radiation pattern from the direction of a desired signal, thus improving the signal-to-noise ratio (SNR) (Dey, Ashour, 2018).

Two important terms associated with array arrangement is beamforming and the direction of arrival (DOA). Beamforming is the procedure of estimating DOA and can be defined as a process of changing the phase and amplitude of signals received by an array of sensors (in this case microphones). The goal of beamforming is to enhance the signals from one direction while suppressing the other directions, to make the received signal specific to a direction. There are two major types of beamforming: data-dependent and data-independent. Data dependent methods usually change parameters based on the received signal example are adaptive or optimal, phase-shift frequency beamforming. Data-independent (or fixed) beamforming have fixed parameters; examples include delay-and-sum, filter-and-sum, subband, and minimum variance distortionless response beamforming (Mathworks, n.d.). The DOA, on the other hand, is a process of determining the direction (for example, in degrees) in which a received signal was transmitted. The degree of accuracy of the estimated DOA is affected by the performance of beamforming, thereby making beamforming and DOA interdependent on each other.

3. Principles of microphone-based monitoring

Microphone-based health monitoring systems utilize the body's natural sounds (signals), such as breathing, heartbeats, and coughing, to obtain vital physiological data. By detecting these acoustic signals, these systems can constantly and non-invasively monitor an individual's health, as a suitable alternative to contact-based devices. Microphones are sensitive to the vibrations caused by physiological events like airflow during respiration, heart valve closures, or even vocal cord vibrations. The vital signals monitored by the microphones include heart rate, respiratory rate, snoring and coughing.

3.1. Signal processing techniques

The accuracy and effectiveness of a microphone in monitoring vital signs depend largely on the parameters of the microphone itself and possibly on the preamplifier working with it. These factors should be well supported by the signal processing method adopted. Recorded information contains noise and other unnecessary data, necessitating the use of filtering techniques to extract important signals.

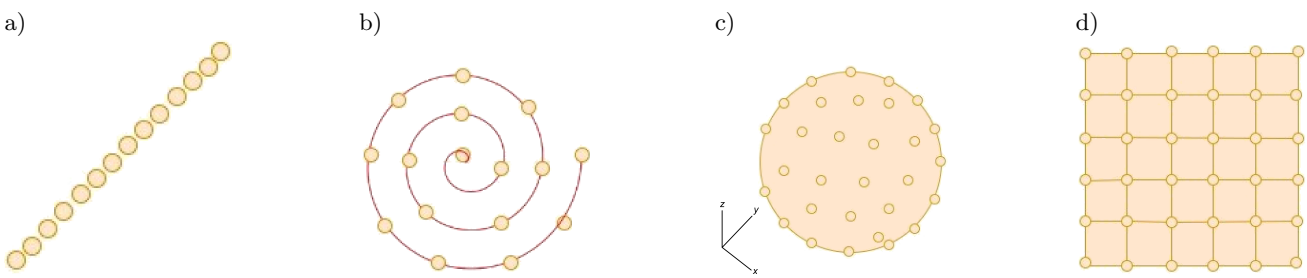

Fig. 1. Different array arrangements: a) linear array; b) spiral array; c) circular array; d) planar array.

3.1.1. Noise filtering and amplification

A significant challenges in microphone-based monitoring is the capture of background noise (Llorca-Bofi *et al.*, 2024; Paul *et al.*, 2023). This noise can degrade the quality of the acquired signal, making it difficult to the isolate desired signal. Noise can be addressed using numerous filtering techniques. For example, band-pass filter can clearly separate breath signals from noise, as the frequency of the breath signal is between 100 Hz and 1000 Hz while heart sound ranges between 20 Hz to 200 Hz (Han *et al.*, 2023). Other filtering methods such as low pass and high pass filters can also be applied to recover a desired signal. Amplification is essential for enhancing low-amplitude signals, such as shallow breath signal.

3.1.2. Adaptive filtering

Adaptive filtering is a signal processing technique commonly used in noise cancellation, system identification, channel equalization and control systems. The major difference between an adaptive filter and other types of filters is its ability to dynamically adjust its coefficients in response to changes in the signal environment (Arenas-Garcia *et al.*, 2021). This dynamic adjustment makes it suitable for processing a non-stationary signal, such as the breath signal. One common example of a adaptive filter is the adaptive line enhancement (ALE). ALE uses adaptive filters with dual roles: predicting the narrowband component of a noisy signal and enhancing them while eliminating broadband noise. ALE assumes that the narrowband signal is either sinusoidal or periodic, allowing it to exploit the time correlation in the narrowband signal to distinguish between the original or desired signal from the uncorrelation broadband noise. To improve the quality of the desired signal, ALE uses the previous input to separate the narrowband components from the broadband noise. The basic components of ALE include the input signal, the delay lines, the adaptive filter, and the computed error signal. The use of ALE in microphone-based, non-contact health monitoring is important, as one of the challenges associated with microphones is their tendency to pick up background noise along with the desired signal. ALE can be applied to solve this problem (Atkins *et al.*, 2021).

3.1.3. Time-domain and frequency-domain analysis

Signal features can be extracted using either time-domain or frequency-domain analysis. The time domain describes changes in a signal amplitude with respect to time and is useful for detecting breath cycles or heartbeats. On the other hand, frequency domain analysis, examines the signal energy's distribution across a range of frequencies, which helps identifying specific physiological signals characterized by specific frequencies (Rangayyan, 2015). A common example used in frequency domain analysis is the fast Fourier transform (FFT), which coverts a time domain to the frequency domain for more detailed analysis of its frequency components (Henry, 2023). Furthermore, the time-frequency distribution (TFD) combines both time and frequency domain information, providing a more comprehensive analysis when both time and frequency domain information are needed simultaneously.

3.1.4. Machine learning and AI integration

Recent advancements in microphone-based non-contact health monitoring system focus on integrating machine learning (ML) and AI. These algorithms enable the model to identify, classify and interpret physiological signals. For example, deep learning models such as convolutional neural network (CNN) and long short term memory (LSTM) networks are used to distinguish normal and abnormal breath or heartbeat patterns (Li, Qian, 2024; Roseline *et al.*, 2024). Additionally, these algorithms can handle large datasets and learn from previously collected physiological signals, improving accuracy. Numerous ML- and AI-based methods have been used for the identification and classification of different types of coughs, wheezes or heart signals (Ferrante *et al.*, 2020; Orlandic *et al.*, 2021; Pramono *et al.*, 2019; Renjini *et al.*, 2021). In a case when microphone records patient's respiratory signal, the raw data serves as an input to the AI-powered system, which filters out (remove) noises, identifies key features, and classifies the data based on the trained model. This facilitates real time diagnosis of diseases associated with breath and heartbeat signals.

3.1.5. Pattern recognition and feature extraction

Pattern recognition plays a crucial role in identifying acoustic signal. The algorithm detect repetitive patterns in the signal, such as peaks in the amplitude or the periodicity of heartbeats and breathing cycles. The wavelet transform is a commonly used feature extraction method, and it decomposes complex signals into simpler components, allowing unique characteristics that may indicate the presence or absence of diseases to be clearly identified (Taghavirashidizadeh *et al.*, 2022).

4. Beamforming based methods

Beamforming can be defined as the process of combining multiple signals from microphones in an array to amplify sound in a specific direction. Beamforming can be combined with other approaches, such as radar systems and cameras, to locate targets (Xiong *et al.*, 2023; Wang *et al.*, 2023). To detect a signal in a specific direction, the beamformer controls the phase and amplitude at the transmission end. In non-contact vital

sign monitoring, beamformers ensure accuracy measurement of vital sounds and allow monitoring of multiple subjects at the same time. Frequent body movementa and noise are among the main factors hindering beamforming. This section reviews literature that has adopted beamforming.

A dynamic convolution-transformer neural network (DYCTNN) for sound source localization using functional beamforming was proposed by Zhang *et al.* (2024). Dynamic convolution and self-attention techniques were used to capture the spatial distribution of sound sources. The model was trained and tested using a dataset generated via acoustic simulation on a 2 m × 2 m plane with a 60-channel spiral microphone array and one to five monopole sources producing sound fields at various frequencies. Xiong *et al.* (2023) utilized beamforming by combining a phased array of an antenna and a double-phase shifter (DPS) to adjust the magnitude and phase of the transmitted signal. Beamforming allowed for simultaneous monitoring of numerous people with minimal target interference. Actuators were utilised to simulate human chest movement, while an omni-antenna was employed to generate and receive signals. This method worked well; however, adding antennas make this system too complex.

Sun *et al.* (2022) used a phase-shifting technique for transmitting beam formation and digital beamforming for optimal spatial filtering at the receiving end. The method utilized a frequency-modulated continuous wave (FMCW) radar with 9 transmitting and 16 receiving channels. Digital beamforming was designed to obtain optimal spatial filtering at the receiving end, enhancing the capability of multi-person detection. The arctangent demodulation method was used for phase estimation, and phase unwrapping was thereafter applied to address phase ambiguity. The proposed method was able to detect targets within the range of 1.8 m to 12 m. Hall *et al.* (2015) developed the phased array non-contact vital sign (NCVS) sensor system with an autonomous beam steering algorithm, implemented in LabVIEW. The selected phased array arrangements were tested, and data samples were gathered to assess the performance of the autonomous beam steering algorithm. The results showed that heart rate measurement accuracy was approximately 95 % within 5 bpm, and the automatic beam steering algorithm achieved an accuracy of 94.36 % within 5 bpm with a 2.82 bpm standard deviation.

Wang *et al.* (2023) introduced the dualforming-based method that combined both spatial and frequency domain beamforming to improve the signal-to-noise ratio (SNR) across multiple subject locations. The multiple subtle signal classification (MUS2IC) approach was used to separate subjects with subtle movements from static objects. Empirical mode decomposition (EMD) was used to extract heartbeat patterns by decomposing the cardiac frequency response (CFR) streams into separate intrinsic mode functions (IMFs). The method measured heart rate within a 10 m range, allowing the monitoring of heartbeats of six subjects at the same time. Tashev and Acero (2006) presented a post-processing a microphone array's beamformer output. The algorithm estimated the spatial probability of sound source presence and applied a spatio-temporal filter. Experimental results showed that the directivity index improved up to 8 dB and jammer suppression up to 17 dB at the angle of 40° from the sound source.

5. Microphone sensor based method

A microphone can detect vital signals in both contact and non-contact modes. The latter produces less noise since the sensors are not in direct contact with the subject's body. This section explores various studies conducted in this area. A simple diagram of the microphone-based method is shown in Fig. 2.

Chen *et al.* (2015) presented a microphone position calibration approach to distribution microphone arrays, combining an acoustic energy decay model with the time difference of arrival (TDOA) method. The method first estimates the coarse distance between the microphone and the sound source, followed by TDOA to find the accurate distance within a specific range near the coarse distance. The microphone's position is determined using the least mean square error estimate approach, which yields high positioning accuracy, steady calibration performance, and low processing complexity. Qian *et al.* (2018) employed FMCW sonar to send a chirp signal and calculated the spectrogram of the baseband signal to extract vital signals such as breath rate, heart rate, and individual

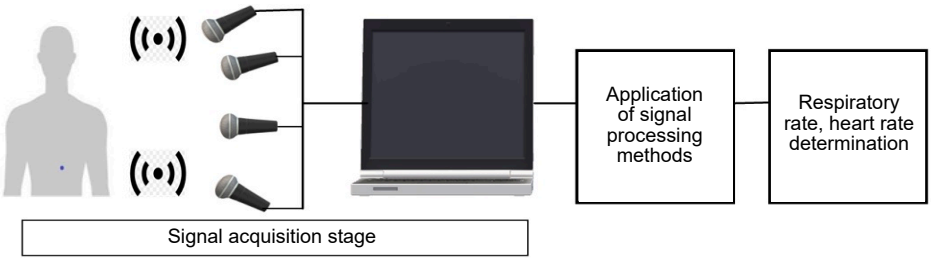

Fig. 2. Typical diagrammatic representation of vital signs monitoring system setup using microphone.

heartbeat from the acoustic signal phase. The method downsampled the FMCW signal to baseband and continually monitored the signal phase in the spatial bin containing vital motions. The use of dual microphone enhanced the performance of the system.

Valipour and Abbasi-Kesbi (2017) monitored heartbeat and respiration rate using a phonocardiogram based miniature wireless acoustic sensor with two capacitor microphones, a microprocessor, and a transceiver operating at 2.54 GHz in the industrial, scientific, and medical (ISM) band. The sensor was placed on the volunteer's chest, and ECG signals were acquired. The findings showed root-mean-square errors (RMSEs) of less than 2.27 bpm for heartbeat and 0.92 bpm for respiration rate, with standard deviation of less than 1.26 for heartbeat and 0.63 for respiration rate. Overall, the developed approach is contact-based. Tran *et al.* (2014) used a hybrid hardware-software technique to detect an infant's vital signs, using an infrared non-contact temperature sensor and a microphone-based breathing sensor. The system was designed in a hardware description language (HDL) and implemented on an field-programmable gate array (FPGA) board. The developed device identified the infant's vital signs when tested on the Altera DE2-115 FPGA board.

Taniguchi *et al.* (2023) presented a vital sign monitoring system for dogs based on the MEMS microphone and the Raspberry Pi wireless system. To extract the heart rate, they first removed the DC offset from the obtained data, then transformed it using the short time Fourier transform (STFT), and finally applied the fifth-order Butterworth bandpass filter. The filtered data was then normalised, and the heart rate was calculated by counting amplitude peaks within a specific time frame. The heart rate extraction technique includes calculating the number of data points and amplitude thresholds, as well as computing the distance between peaks. The heart rates acquired during the surgery were monitorable every second, with an average heart rate of 110 bpm.

Dafna *et al.* (2015) proposed a non-contact microphone-based polysomnography (PSG) to measure breathing noises and estimate breath rate during sleeping. Adaptive noise reduction techniques was used to suppress background noise and non-periodic spectrum components were filtered out by a periodicity augmentation module. The BR module was the final stage, and it estimated BR based on the filtered signal. The system was tested on 204 individuals who participated in an in-laboratory in the study. The Pearson correlation coefficient between the two techniques was $R = 0.97$, showing a strong relationship. An epoch-by-epoch BR comparison revealed a mean relative error of 2.44 % and Pearson correlation of 0.68, demonstrating good agreement between the audio-based BR estimation and the gold-standard respiratory belts.

Wang *et al.* (2021) presented a low-cost, contactless heartbeat monitoring device based on a commodity speaker and a microphone array. Acoustic impulses are transmitted by a speaker and received by a microphone array to estimate the human heartbeat. Passive beamforming and frequency domain filtering were used to improve the quality of the signal accuracy. A wideband time-delay approach was also used to predict the DOA of the target-reflected signal. The prototype monitors heart rate at a distance of 1.7 m, with an estimation error of 0.5 bpm. A wearable microphone sensor based on the adaptive windowing technique was employed by Zhang *et al.* (2024) to estimate heart rate. The method used a spectrogram to derive an initial estimate and calculate the optimal window length based on frequency resolution and physiological constraints. A one-step autoregressive model was used to correct estimates, thereby improving the heart rate measurement accuracy by ±2.8 bpm. The developed method was tested on a group of 26 healthy subjects. Ashraf and Moussavi (2024) designed a piezoelectric surface microphone placed at the suprasternal notch to capture tracheal breathing sounds. This device produced clear respiratory waveforms with minimal sensitivity to ambient noise. A wearable accelerometer microphone (Gupta *et al.*, 2021) captured lung sounds and chest-wall motion to derive respiratory patterns in hospitalized patients with COPD, pneumonia, etc. These contact sensors can measure both breath sounds and rate with high fidelity, even amid patient motion or background noise; for example, the piezo sensor showed negligible degradation across frequency bands when noise was present.

6. Smartphone and contact based methods

Smartphone technology started in 1992 (Tocci, 2024), and it has surpassed expectations, particularly in the development of applications that can run on smartphones. A significant contributor to this success is the microphone, which has helped acquisition of data for various applications, including those focused on vital sign monitoring. Smartphones are now capable of monitoring vital signs such as heart rate, respiratory rate, blood pressure, and blood oxygen saturation, whether through contact-based or non-contact methods. The section focuses on the literature that has used microphones installed in smartphone for vital sign monitoring.

Kavsaoğlu and Sehirli (2023) captured audio signals from the heart and trachea, resulting in a dataset for detecting inhalation and exhalation circumstances. Two methods were used to obtain these signals: one involving heart sound and the other involving trachea sounds. The audio signals were classified into inhalation and exhalation phases using ML models. The highest accuracy and performance

were achieved using a majority voting strategy with k-nearest neighbour, random forest, and support vector machines. Doyle (2019) used a flat adhesive acoustic sensor and the TASCAM DR-40 Digital Recorder to record bioacoustic data. Recordings were taken from multiple of locations, including the neck, external ear canal, oxygen mask, as well as a leak-free microphone attached to a laryngeal mask airway. Audacity, an open-source digital audio editor and recording programme, was used to analyse breath sounds and apply digital filters.

Lee *et al.* (2023) used an array of MEMS microphones to record lung sound waves, which were converted into acoustic images. The system's performance was assessed using waterbags to stimulate airway blockages, and its accuracy was compared to that of digital stethoscopes. The proposed method demonstrated better detection of lung conditions, with a room square error of 0.28 and SNR of 7 dB. LoMauro *et al.* (2022) introduced a semi-automatic, robust pre-processing for respiratory data analysis using functional data analysis (FDA) techniques. The approach involved separating, detecting outliers based on time-duration, amplitude, and shape, and clustering breaths using K-medoids for different breathing patterns. The proposed methodology showed an error rate of less than 5 % for minimum detection and outlier removal.

Chauhan *et al.* (2017) developed a framework that combines smartphone acoustic sensors to identify breathing phases and estimate biomarkers. Breathing data was collected from pulmonary patients and healthy individuals using Samsung Galaxy Note 8 smartphones, chest bands, and spirometers. The system achieved 77.33 % accuracy and over 90 % accuracy in estimating respiratory rate and other biomarkers. Shih *et al.* (2019) developed a real-time breathing detection algorithm with low latency, running on a smartphone. To train and evaluate the developed system over 2.76 million breathing sounds from 43 participants was captured, and the system achieved 75.5 % accuracy in detecting breathing phases using a combination of attention-based LSTM models and CNN-based extraction modules. Wang *et al.* (2018) used a correlation-based frequency-modulated continuous wave (C-FMCW) approach for monitoring human breathing via audio signals. The common speaker and microphone components found in most homes were used. The system accurately identified subjects' respiration in a variety of environments, including different rooms and subject sleep positions. Khodaie *et al.* (2021) developed a system that records respiratory sounds from the upper airways using microphones implanted in a breathing mask. The study discovered a strong correlation (coefficient of 0.9) between acoustic features of respiratory sounds and respiratory metrics such as the peak flow and average flow.

Fang *et al.* (2023) proposed the identity-based respiration monitoring system for digital twins enabled healthcare (IDRes). The respiration rate was estimated by tracing the changes in the phase of the sonar signal and detecting the doppler frequency shift to capture chest motion characteristics. Experimental results showed 93.3 % recognition accuracy and the mean detection error of 0.49 bpm.

Xu *et al.* (2020) proposed the BreathListener, a system that monitors breathing in driving scenarios using audio devices on smartphones. The method captured fine-grained breathing waveforms in driving scenarios. The device used the energy spectrum density (ESD) of acoustic waves to record breathing processes in driving conditions. BreathListener used background removal and variational mode decomposition (VMD) to remove interference from driving settings while extracting the breathing pattern from the ESD signals. The retrieved breathing pattern was then translated into the Hilbert spectrum, and the fine-grained breathing waveform was generated using a deep learning architecture, based on generative adversarial networks. Chara *et al.* (2023) developed an FMCW-based acoustic system on a smartphone by emitting and receiving high-frequency chirps, the phone tracks tiny chest displacements. In trials this approach achieved extremely high accuracy – a median breathing-rate error below 0.15 breaths per minutes across various conditions. A smartphone-based contact method. Phokela *et al.* (2020) used a headset microphone under the nose to record nasal airflow sounds: it achieved respiration-rate errors less than 10 % even in noisy environments, demonstrating feasibility for home use.

Nemcova *et al.* (2020) estimated the heart rate, blood oxygen saturation (SpO2), and blood pressure (BP) using smartphone sensors. HR and SpO2 were determined by generating a photoplethysmogram (PPG) from the camera data, while BP was measured by calculating the pulse transit time value from the PPG and recording a phonocardiogram (PCG) via the microphone. The results showed mean absolute errors (MAE) of 1.1 % for SpO2 and 1.4 bpm for heart rate. Vincent *et al.* (2023) presented a multi-target blind source separation technique based on a single sonar. The use of the freqency hopping (FH) technique within the ULCW (Ultra-CW) scheme helped to minimize the effects of frequency-selective fading (FSF) and intersymbol interference (ISI) in the baseband, thereby improving the accuracy of acoustic signal transmission. The combination of continuous wave (CW) and FMCW signals in the ULCW scheme enhanced the transmission of energy from the smartphone, enabling accurate acoustic signal propagation over long distances. Doheny *et al.* (2023) developed a method to predict respiratory rate and exhale length from smartphone captured audio data. The method required cal-

culation of the audio signal's basic frequency and detection of individual exhales with adaptive thresholding. Exhale boundary timings were optimised with adaptive physiological thresholds. The respiratory rate was determined by identifying peaks and troughs in the respiratory inductance plethysmography (RIP) signal, and exhale durations were calculated as the time between each peak and the next dip in the RIP signal. The RIP respiratory rate was utilised as the standard against which the audio respiratory rate was measured. The fundamental frequency of the respiration envelope was found as the frequency corresponding to the first peak in the harmonic product spectrum above 0.09 Hz. Other active acoustic methods use smart speakers to monitor breathing or heart rate, though these are mostly prototypes or proof-of-concept. The advantage of these non-contact methods is comfort and convenience and suitability for home or telehealth. However, they require a device (smartphone or speaker) close to the subject and can be sensitive to environmental noise or interference. Thick clothing, bedding, or a distance beyond 2 m–3 m can degrade signal, so practical use often means limiting the scenario.

7. Hardware based methods

This section examines approaches that incorporated hardware components, whether handheld or not, with the capability to determine the respiration rate of subjects.

Al-Ali and Lee (2012) patented a physiological acoustic monitoring system that collects physiological data from an acoustic sensor and generates respiration-related parameters in both real-time and non-real time. The system processes data by downsampling to provide raw audio of breathing sounds, and compresses it for futher analysis. Wang *et al.* (2023) presented the MultiResp, a multi-user respiration monitoring system that detects chest movement using acoustic signals. The system captures acoustic signals reflected from participants' chests, allowing for robust respiration monitoring even when subjects are facing away from the transceiver or blocked by barriers. MultiResp extracted fine-grained breath rate and phase differences between participants to differentiate breath waves with similar rates and adjust to dynamic variations in the number of monitored subjects. However, MultiResp fails when the sound pressure is less than 55 dB or when there is body movement which causes significant alterations in the multipath signals, causing erratic fluctuation of the channel impulse response (CIR).

Abbasi-Kesbi *et al.* (2018) presented a wireless acoustic sensor that used a phonocardiogram to detect heartbeat and respiratory rate. The system comprises a processor, transceiver, and two capacitor microphones for capturing heartbeat and respiration rate. The technology also measures breathing rate with a capacitor microphone placed near the mouth. The wireless acoustic sensor demonstrated high accuracy in predicting heartbeat and breathing rate, with RMSEs of less then 2.27 beats/min and 0.92 breaths/min, and standard deviations of less then 1.26 and 0.63, respectively. The system's sensitivity and specificity in recognizing PCG sounds ranged for S1 to S4 at 98.1 % and 98.3 %, respectively, representing a 3 % improvement over earlier work. This method accurately recorded heart and respiration rate in a variety of circumstances, including resting and breath-holding, with consistent results across numerous volunteers.

Wan *et al.* (2023) introduced a continuous multi-user respiratory tracking system designed for household settings using acoustic based commercial off-the-shelf (COTS) sensors. The system employed multi-stage algorithm to isolate and recombine respiration data from different paths to calculate the respiration rate of several moving persons. By utilizing features from multiple dimensions to distinguish between users in the same region, and applying Zadoff–Chu (ZC) sequences with optimal auto-correlation, it differentiates user pathways. The system transmits the ZC sequence modulated by a sinusoidal carrier as the transmitted sound signal, with its detection range and bandwidth determined by the length of the ZC sequence and frame length. The experimental results showed that RespTracker's two-stage algorithm can differentiate the respiratory pattern of at least four subjects over a three-meter distance.

8. Artificial intelligence based method

This section reviews studies that have adopted ML techniques using a microphone as the primary signal acquisition method. Figure 3 illustrates ML-based method.

Xie *et al.* (2023) utilised an autoencoder (AE) neural network to quantify the residual between the original and reconstructed signals, which can increase the end-to-end (e2e) respiration monitoring accuracy by a factor of 2.75 when compared to the baseline. Their approach employed deep learning techniques, combining an autoencoder neural network and a self-supervised learning to quantify signal quality. The use of radio frequency quality (RF-Q) further enhanced respiration monitoring accuracy. However, large volumes of training data are required for deep learning algorithms and the need for manual labelling, as training datasets for DL techniques is typically not publicly available.

Liu *et al.* (2021) proposed a reverberation aware network (RAN) algorithm for improving the robustness of DOA estimation. The algorithm used the beam cross-correlation (BCC) as an input to a deep neural network (DNN), explicitly characterizing reverber-

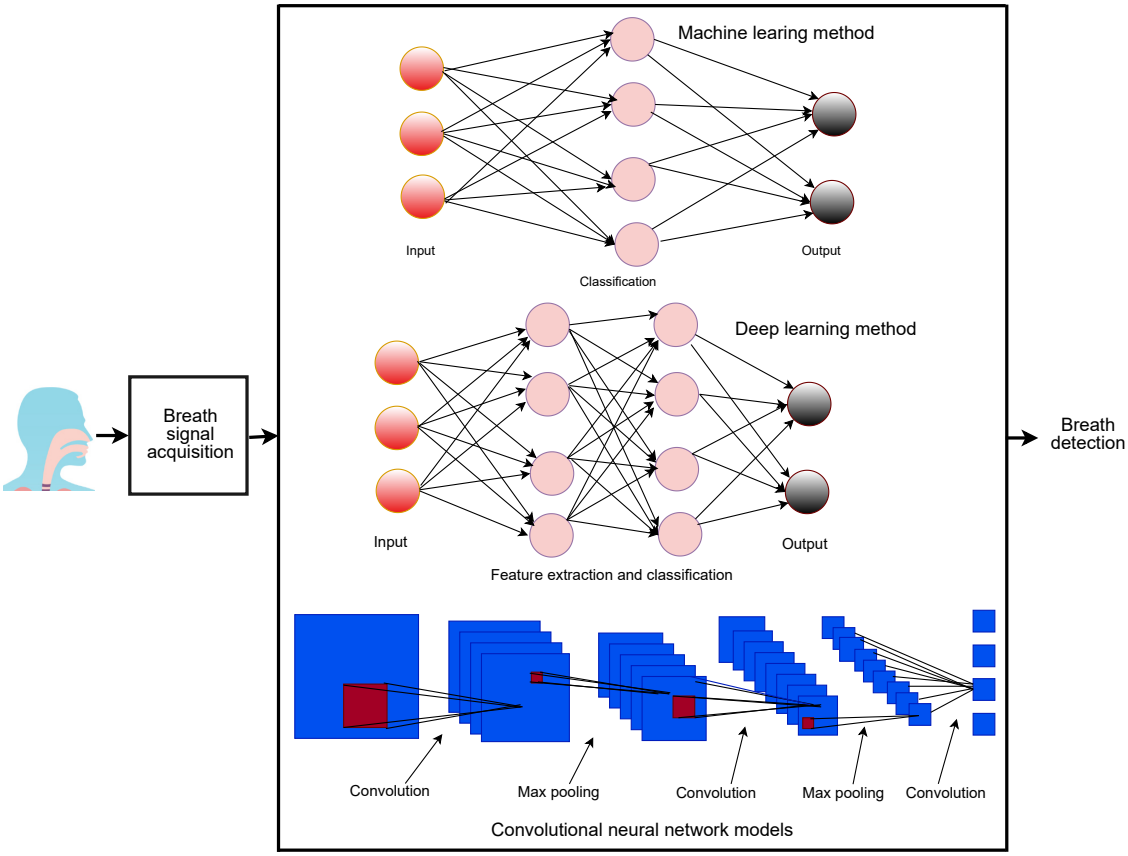

Fig. 3. Machine learning based method.

ation in the captured speech signal. The classic beamforming algorithm was used to generate beamforming outputs, the observed signals, which was then used as a reference for reverberation identification. The filter-sum (FS) beamforming algorithm was adopted for beamforming processing. Numerical simulations were based on virtual room environments generated with a reverberation model, as well as practical experiments under physical room environments, to evaluate the performance of the proposed method. The impact of different environments on the performance was evaluated by conducting experiments with different noise levels and source distances. In addition to the aforementioned research, some studies have also combined two methods, such as beamforming with ML (Zhang *et al.*, 2024) and smartphone with ML (Kavsaoğlu, Sehirli, 2023; Shih *et al.*, 2019; Xu *et al.*, 2020). Despite the promising application of ML in different fields, this area is underexplored especially when using a microphone as the non-contact health monitoring method.

9. Challenges and solution

Using microphones for signal acquisition in medical applications presents several challenges, with noise and interference being the most significant. To address these issues, some techniques have been proposed, including the use of adaptive noise reduction algorithms (Abed *et al.*, 2022; Thomsen, Du, 2020; Meyer *et al.*, 2020; Wu *et al.*, 2020; Wang, Qiu, 2020), directional microphones (Fischer, Puder, 2012; Kanamori, Terada, 2016; Nongpiur, 2018; Park *et al.*, 2020), and the application of ML (Jain, Hera, 2019; Shiozawa *et al.*, 2020; Takenaka, Ozawa, 2022). While these three methods have been independently used in the literature, this review suggests an integrated method that combines these approaches. In this proposed solution, adaptive noise reduction reduces inherent noise from recordings, directional microphones capture signals from a single direction or a patient, and ML processes the signals to minimize noise interference more effectively. Another challenge is the urgency with which some respiratory data are required to make informed decisions. High latency or processing delays can be problematic, this issue can be addressed by using edge computing, which processes data locally, or by employing optimized algorithms for real-time data processing. These suggested methods can significantly improve the responsiveness and reliability of microphone-based non-contact monitoring systems in medical applications. Apart from the above, other challenges with microphone include privacy, data security and technical implementation. Although data

privacy and security were not mentioned by some of the articles reviewed. However, they remain one of the challenges associated with the use of microphones and other audio-based signal acquisition methods. Audio recordings should be treated with utmost security, as they reveal sensitive health information. Alqudaihi *et al.* (2021) suggested that only numeric features should be extracted from heart and respiratory signals and that data transmission should be anonymized summaries. To further enhance data privacy and security. Alqudaihi *et al.* (2021) also recommended implementing blockchain-based audit logs or federated learning techniques. Future directions could focus on the development of specialized contact microphones and the adoption of AI-based denoising and data encryption algorithms to improve the reliability and security of microphone-based monitoring systems. Moreover, privacy-preserving hardware innovations, such as MicPro proposed by Xiao *et al.* (2023) alongside the end-to-end encryption protocol used in some social media messaging applications – can address these issues adequately. Overall, research into the suggested solutions could enhance the performance of microphones as vital sign monitoring systems.

10. Conclusion

This review has presented the potential of microphone-based systems for non-contact sign monitoring. The transition from simple acoustic sensors to the adoption of intelligent health monitoring was made possible by technologies such as beamforming, ML, and smartphone integration. These systems have evolved from simple signal-capturing devices to sophisticated devices capable of detecting complex physiological patterns. Non-contact health monitoring systems can leverage these innovations, such as the integration of deep learning algorithms like CNN, RNN, or LSTM (Acharya, Basu, 2020; Thakur *et al.*, 2022). Although some research has been done in this area, the accuracy and real-time application of ML-based methods can be further improved through enhanced data collection processes, hybrid deep learning models, better feature extraction methods, and the use of microphone arrays instead of single microphones. Future directions could also focus on leveraging smartphone-based applications and cloud-based platforms to improve access, accuracy, and reliability while addressing other challenges associated with microphone-based systems.

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Conflict of 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.

Authors' contributions

Abiodun Ernest Amoran conceptualized the study and wrote the original draft; Dariusz Bismor supervised the research, provided guidance, and reviewed the manuscript. All authors reviewed and approved the final manuscript.

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