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State of the Art Review of Wearable Devices for Respiratory Monitoring

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ABSTRACT Respiratory frequency and volume are essential physiological signals for diagnosing and managing respiratory diseases such as asthma and chronic obstructive pulmonary disease (COPD). Wearable devices have emerged as a transformative tool for continuous, non-invasive respiratory monitoring and data portals, providing massive real-time data critical for both clinical and home settings. This state-of-the-art review delves into the advancements and applications of wearable respiratory monitoring devices, specifically focusing on inertial measurement units (IMUs), piezoresistive sensors, and optical fiber sensors. Detailed analyses of sensor designs, sensing methods, and clinical applications are presented, highlighting key studies such as the development of low-cost IMU devices for breathing frequency monitoring and the integration of piezoresistive sensors for real-time respiratory rate detection. This review identifies major challenges, including power efficiency, ergonomic design, data accuracy, and data privacy concerns, and also introduces innovative solutions proposed in recent research. Future research directions are suggested to address these challenges and further enhance the capabilities and reliability of wearable respiratory monitoring devices. This review underscores the potential of wearable technology to improve patient outcomes and resource cost burdens through early diagnosis and data creation towards continuous health monitoring and artificial intelligence applications.

INDEX TERMS Wearable respiratory monitoring; Inertial measurement units (IMUs); Piezoresistive sensors; Optical fiber sensors; Chronic obstructive pulmonary disease (COPD); Non-invasive monitoring; real-time health monitoring; Respiratory frequency detection; Continuous health monitoring; Sensor technology in healthcare.

INTRODUCTION

Chronic Respiratory diseases (CRDs) are among the most prevalent noncommunicable diseases globally, impacting over 545 million people as of 2017 [1]. The most common CRDs are asthma, chronic obstructive pulmonary disease (COPD), occupational lung diseases, and pulmonary hypertension. According to World Health Organization, CRDs account for 4.1 million deaths annually, comprising approximately 10% of all noncommunicable disease fatalities. Within England, the National Health Service (NHS) has reported chronic respiratory disease as the most significant cause of death. As such, CRDs impose a substantial economic burden globally [2]. In particular, asthma and COPD cost the NHS an estimated £3 billion and £1.9 billion each year, respectively, demonstrating the overwhelming financial strain these conditions place on the medical system [3, 4]. Given this burden, steps must be taken to utilize technology and new discoveries to improve prevention, treatment, monitoring, and chronic management of these conditions [5].

Traditionally, the diagnosis and treatment of respiratory diseases involves invasive and time-intensive methods, such as spirometry, plethysmography, pneumography and capnography [6]. There are many situations in which the sudden-onset, location, and urgency of respiratory distress may not allow for the use of such costly and prolonged methods [7]. As such, it may be critical to use other more accessible and cost-effective methods to assess a patients' physical and respiratory health. Respiratory rate (RR) may be one such metric to facilitate understanding health conditions quickly and even predict the onset of serious clinical events [8, 9]. RR may also serve as a metric to predict the onset of serious clinical events including risk assessment for cardiopulmonary arrest and post-acute myocardial infarction [10-12]. Some have even shown that RR is the most optimal index compared to other vital measurements to identify high-risk patient groups [13].

As medicine evolves towards a more preventative healthcare framework, there is a growing emphasis on continuous health monitoring and assessment beyond the hospital walls. The delivery of healthcare screening, diagnosis, and monitoring from home is particularly relevant in an aging population with a greater rate of chronic medical conditions.

Wearable devices play a crucial role in meeting the demand for this non-clinical, continuous health monitoring and show significant potential in healthcare [14-16]. The rapid advancement of wearable technology, fueled by the simultaneous advancements in artificial intelligence (AI) and large language models (LLMs), has led to a diverse array of commercially available devices capable of health monitoring. These devices enable patients to continuously monitor their RR, heart rate (HR), apnea conditions, and more from the comfort of their homes. Such innovations not only bring significant convenience to daily life but also profoundly impact the current healthcare landscape [17, 18]. Moreover, with the advancement of Internet of Things (IoT) technology, wearable devices can establish a comprehensive loop of data collection, analysis, feedback, and response. This integrated system facilitates the development of a more intelligent and user-friendly health monitoring and management framework, ultimately enhancing users' health outcomes and quality of life [19-22]. It is worth mentioning that in the study of Mohsen et al., they proposed a new IoT wearable sensor node which was powered by solar energy. In addition, the experiment has proved that the system can continuously monitor the user's important vital signs for a long time, offering a novel solution to the battery life challenges commonly faced by wearable devices and demonstrating the application potential of clean energy in health monitoring [23, 24].

CDRs offer a uniquely rich application for wearable technology which can monitor the respiratory function of patients from home [25]. The portability and comfort of today's wearable devices allow for the easy collection of large amounts of human physiological signals in a non-invasive way. This capability is further enhanced by advancements in sensor miniaturization technology, allowing for the production of increasingly smaller, ergonomic, convenient, and more efficient devices [26]. While numerous advancements have been made in the collection of respiratory data from home in a short amount of time, there are many barriers to overcome including battery life, material allergy, Bluetooth compatibility, usability, and data privacy.

A thorough background is presented on the development, testing, and analysis of respiratory wearable devices. Ultimately, a foundation is provided for the growth of future respiratory wearable device development. Such devices have the potential to reduce burden on the primary care system, facilitate health monitoring for patients in remote settings, and improve access to pulmonary screening.

II. WEARABLE DEVICES BASED ON IMU SENSOR

An inertial measurement unit (IMU) is an electronic device which typically comprises sensors like accelerometer, gyroscope and sometimes maybe contain a magnetometer. Magnetometer measures the strength of magnetic field and direction in the surrounding environment. Its working principle involves detecting the effect of magnetic field on a magnetically sensitive material within the device, which then generates an electrical signal proportional to both the strength and direction of the magnetic field. Accelerometer measures the object's changes in acceleration and is commonly based on Micro-Electro-Mechanical Systems (MEMS) technology. The working principle of an accelerometer mainly relies on the displacement of a mass under the influence of external forces, which is then converted into an electrical signal corresponds to the acceleration. The gyroscope measures the object's changes in angular velocity and orientation, and operates based on the Coriolis effect. When the sensor rotates, the vibrating mass experiences a deflection, which is subsequently transformed into an electrical signal corresponding to the angular velocity. Given its compact size and affordability, IMUs are widely used in wearable devices [27]. In the past decade, advancements in electronic sensor technology have significantly improved IMU accuracy. As a result, IMU's are now employed in the clinical setting to measure physical signals, vital signs, and assist in patient recovery [28-30].

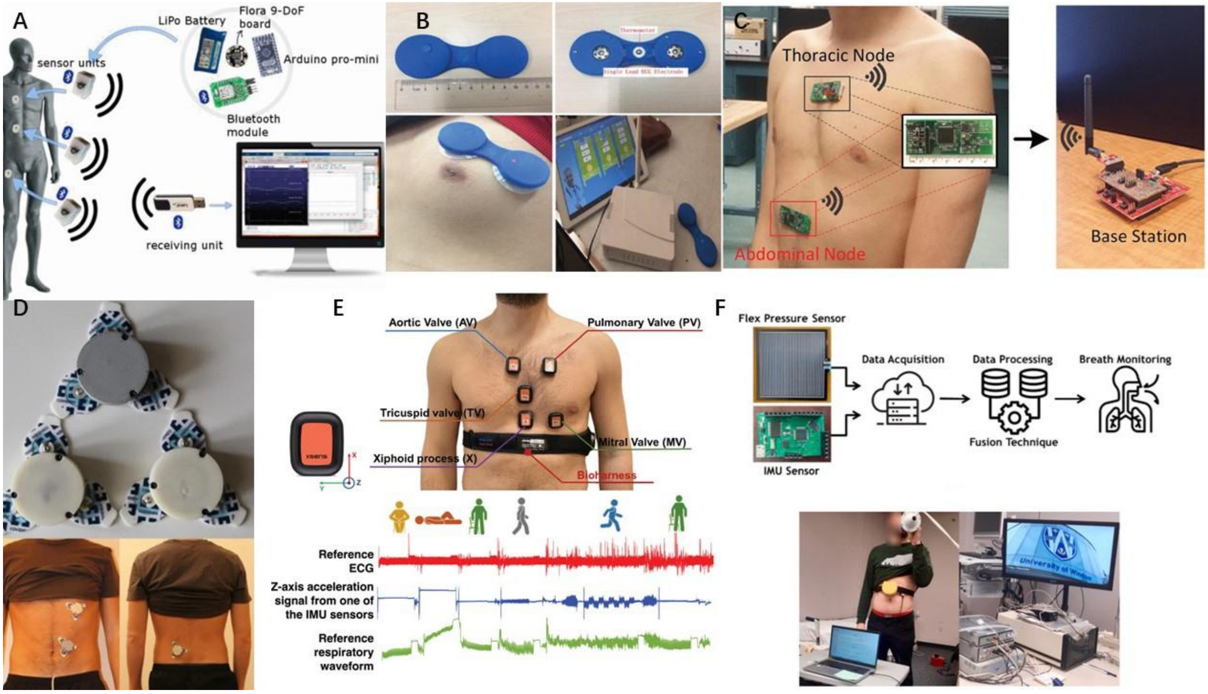

FIGURE 1. **(A) Equipment Components, and the sensor's placement. Each sensor communicates via Bluetooth and connects with a personal computer[31]. (B) The appearance information of the patch wearing device [32]. (C) Placement of two sensor nodes [33]. (Node 1 in black placed on abdomen, node 2 in red placed on thorax) (D) Shape and placement of each sensor [34]. (E) Positions of each sensor and an example of testing Z-axis acceleration records from one volunteer [35]. (F) Conceptual flow and components of the wearable device [36].**

One such application of an IMU device is the Magnetic, Angular Rate, and Gravity (MARG) system which was used by Cesareo et al. to measure the movement signal of breathing. [31] The device consisted of three sensor units and one receiving unit that communicated via Bluetooth to a personal computer, as shown in the figure 1 (A). Data from each sensor were transmitted to a PC via Bluetooth and then analyzed via MATLAB. Data were then resynchronized, smoothed with a five-order moving average filter, and filtered with a 0.05-2 Hz band-pass filter and an IIR Butterworth filter. Among the four components of each obtained quaternion, the one containing the most significant breathing information was selected for identifying each breath in a semi-automatic way. These data were then compared with Optoelectronic Plethysmography (OEP) to assess accuracy. The experiment result showed strong correlation values ($R^2 > 0.88$) and low percentage errors (<5%) for all time-based parameters. This work was, however, limited by small sample size and measurement exclusively under static conditions. Therefore, results may not be generalizable to real-world, dynamic settings.

Wang et al. [32] designed a patch consisting of a 3-axis accelerometer, gyroscope, and an electrocardiogram sensor (Figure 1B), which could be used for real-time and long term monitoring. Device use was monitored using a RR acquisition algorithm which served to recognize, denoise, and reconstruct respiration signals under a dynamic state. This is achieved by use of a Kalman filter followed by the use of a Variance Characterization Series (VCS) to segment the signal to distinguish the deviant slices and locate the abnormal variations. The device was tested on 7 patients and compared with other similar devices, showing that the new algorithm had higher accuracy and robustness (MAE=0.11) than other similar devices. Therefore, the patch sensor wearable device could be used for the long-term monitoring in daily life.

Similarly, Elfaramawy et al. [33] proposed a real-time, low-power wireless wearable measurement system for the detection and monitoring of cough and breath patterns. The monitoring system had two different types of acquisition nodes, a base station, and a PC host (Figure 1C). Acquisition node 1 was located on the chest and was equipped with a microphone and an IMU sensor. Node 2 was located on the abdomen and was equipped with an IMU sensor only. The data obtained by the two sensors was transmitted to the base station through the wireless module and then processed by MATLAB. Firstly, a 3-second window was used to calculate the average displacement angle and remove body movement artifact. The data was then filtered by a 20th order low-pass FIR with a cut-off frequency of 2 Hz. The high-frequency components, associated with artifact, were eliminated by decimating the ventral cavity angle to 5 Hz. The baseline drift was eliminated with a first-order high-pass filter of 0.01 Hz. For cough detection, all data below a predetermined threshold coefficient was set to zero to eliminate the noise floor to detect cough. Although this wearable system had low power consumption, the 100 mAh lithium-ion battery was not enough to meet the needs of the device for extended monitoring sessions. In addition, this equipment could be affected by environmental noise, causing inaccurate measurement.

Existing monitoring systems are generally effective at monitoring RR under static conditions but struggle to accurately monitor RR during dynamic conditions due to motion artifacts. Angelucci & Aliverti [34] proposed a wearable device system based on an inertial sensor, which can estimate the breathing rate under static and dynamic conditions at the same time. Their device was composed of three inertial sensors which were placed on the chest, abdomen and back (Figure 1D) which were used to detect chest wall vibrations associated with breathing. The data was transmitted to the smart device through the ANT communication protocol and processed. Principal component analysis was used to find the component with the largest variance as the respiratory signal. To smooth and denoise the signal, a third order Savitzky-Golay FIR filter was used. After processing, the maximum and minimum values of the signal were detected to determine the respiratory frequency. The study was conducted on 20 healthy volunteers, and this small sample size may not be representing the general population, especially those with health conditions. Expansion of the research experience and sample size and further validation is required prior to applicability in practical healthcare environments.

There is a large body of research showing that IMUs can accurately record mechanical signals caused by chest wall vibrations and respiratory movements, but there is little research on the optimal anatomical placement of IMUs. To address this, Romano et al. [35] used inertial measurement units (IMU) to monitor the heart and lung signals at five different locations of the chest to determine the best monitoring location. The size of the IMU sensor was 36x30x22 mm (Figure 1 (E)). MATLAB was used to pre-process the data obtained by the IMU sensor. Each axis of the five IMU sensors was filtered by a continuous wavelet transform for band-pass filtering. Then, the Hilbert envelope was applied to the signals in the range of 10-40 Hz. Successively, a Butterworth band-pass filter was applied to filter the signal between 0.7-3 Hz to emphasize AO events. To determine the optimal position for the IMU sensor, Welch's overlapped segment averaging estimator was used to obtain the power spectral density (PSD) of the five signals in the frequency domain. Then normalizing the five PSDs and selecting the highest spectrum to evaluate the signal quality at each position and direction. Wearable respiratory monitoring holds potential as a valuable tool for tracking breathing patterns in individuals with obstructive sleep apnea (OSA), a condition characterized by the collapse of the upper airway or cessation of central respiratory drive during sleep. Wearable devices could play a pivotal role in the monitoring and even diagnosis of OSA given that 80-90% of patients are affected but remain undiagnosed. [37, 38] To address this gap, Hayano et al. [39] developed an IMU-integrated smartwatch to detect breathing patterns during sleep associated with OSA. Their algorithm was successful in both identify OSA events and grading their severity. Further testing should be completed in a more diverse cohort of patients with varying age, body habitus, comorbidities, and degrees of OSA.

To address the impact of non-breathing motion on inertial sensors, Zabihi et al. [36] developed and tested novel data fusion technology for wearable multi-sensing patches. (Figure 1F). The device consisted of an accelerometer to detect diaphragm movement associated with breathing and a flexion sensor to detect muscle stretch. IMU sensor data was then used to remove respiration-related artifacts from flexion sensor data, thus enabling accurate respiration detection during body movement. When tested in healthy volunteers (n=6, 3 men, 3 women) in the supine, right lateral, and left lateral positions, the device performed with an accuracy and reliability comparable to gold-standard spirometry methods.

III. WEARABLE DEVICES BASED ON PIEZORESISTIVE SENSOR

The piezoresistive sensor is composed of elastic components, compensation resistors, cables, and shells. The sensor functions by producing a resistance value which changes with the pressure exerted by the outside word. The high accuracy, fast response, low price and long service life of piezoresistive sensors make it an optimal mechanism for medical monitoring including HR, RR, and other physiological conditions [40-42].

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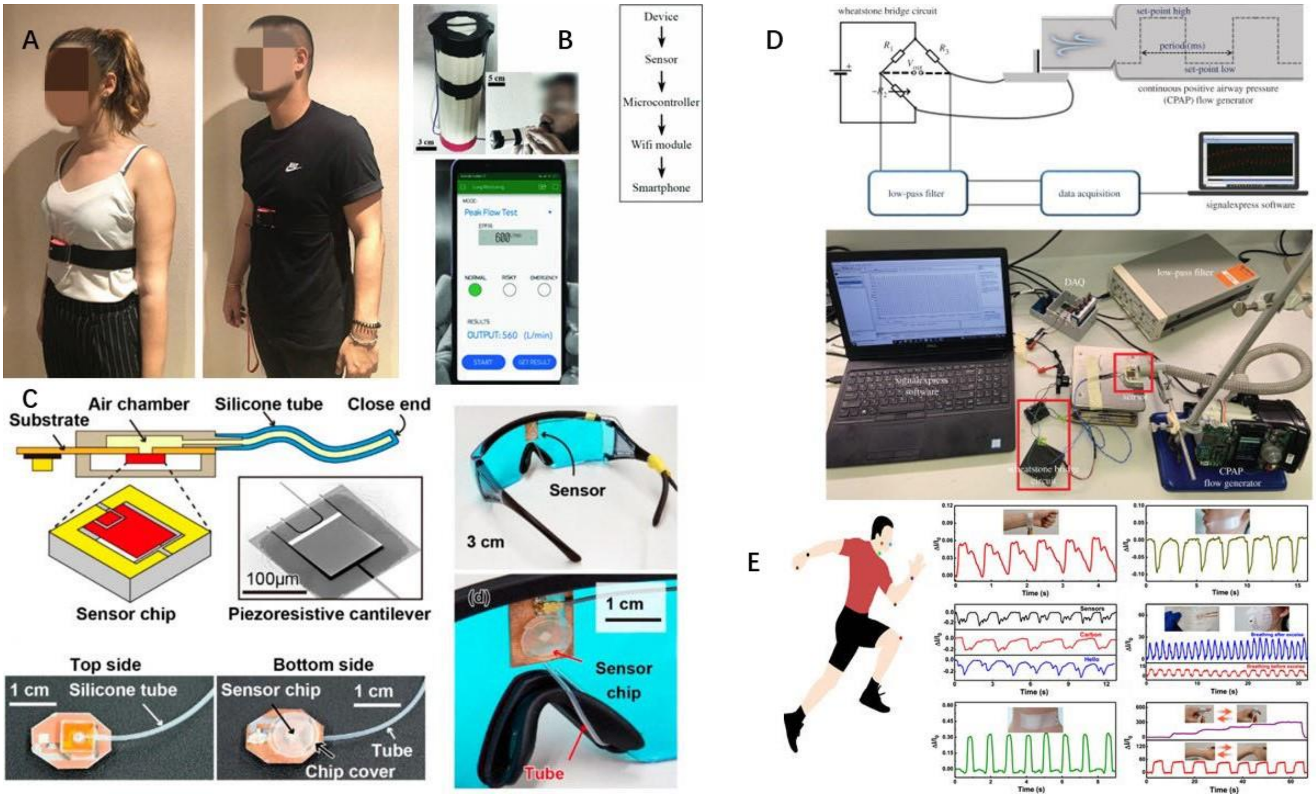

Figure 2. **(A) Wearing method and show that two volunteers wearing the device around chest [43]. (B) 3D printed prototype of the device and the flow chart for mobile application [44]. (C) Schematic diagram of the structural device and physical information diagram of the device [45]. (D) Structural diagram of experimental equipment [46]. (E) Illustration of the sensing device monitoring physiological signals of individual's body [47].**

Chu et al. [48] proposed a compact and user-friendly wearable piezoresistive sensor to monitor breathing rate and volume of those with chronic respiratory diseases. The device was tested on participants under both resting and exercising conditions, demonstrating its capability to accurately measure breathing volume and rate in stationary conditions and ambulatory conditions.

Similarly, Vanegas et al. [43] developed a wearable system comprised of piezoresistive sensors encapsulated in a 3D printed case to monitor breathing rate. The system was tested on 21 participants in different modes and the wearing method showed in the figure 2 (A). The sensing system used a sampling frequency of 50 Hz to obtain test data and transmitted the data via Bluetooth to ultimately be processed offline using MATLAB. First, a 0.5 Hz low-pass filter was applied to eliminate high-frequency noise to smooth the signal. In order to protect the sensor from external interference or interference signals caused by the tester's own movement during the test, linear fitting was performed on each signal to eliminate these interference factors. To obtain respiratory frequency from these voltage signals, the authors proposed two algorithms. One algorithm was based on the time difference between consecutive zero-crossings, using the average time difference between pairs of zero-crossings to calculate RR. The other one was based on continuing the number of crosses by zero. And then calculated the RR by obtaining the number of zero crossings within window time. Their respiratory measurement system showed low errors at different breathing rates, verifying the reliability and effectiveness of the wearable system in practical applications. In addition, it provides open design and data resources to promote further research in this field.

Flexible piezoresistive sensors have also been used to monitor RR and peak respiratory flow rate, demonstrating the feasibility and development potential of this device in the monitoring and management of chronic respiratory diseases (Figure 2B). [44] The experiment used Knudson's standard calculation equation to obtain the expected peak flow rate that was 616 L/min, and divided it into three areas: green, yellow, and red. The green area was 80%-100% of the expected peak flow, indicating that the tester is healthy. The yellow area and red area were 50%-80% and 0-50% of the expected flow value respectively. The yellow area warned of some dangerous situations, and the yellow area indicated that the tester had a health emergency or was suffering from a serious disease. The experimental demonstrated the potential of this device in health monitoring and telemedicine, offering a viable solution for treating and managing chronic lung diseases.

Additionally, microelectromechanical system-based pressure sensors, a specific type of piezoresistive sensor, was used to simultaneously measure RR and pulse fluctuations. [45] This study utilized eyeglasses with a pressure sensor integrated into the nose pads to measure RR and HR through nasal vibrations caused by people breathing and the pulse of the angular arteries as shown in the figure 2 (C). This novel technology was able to consistently detect movement associated with a breath. Specifically, the vibration frequency range caused by breathing movement was approximately 100-400 Hz. As such, the respiratory signal could be extracted by using a 100 Hz high-pass filter. Tests on the volunteers, the effectiveness of the device in measuring pulse waves and RR was verified, providing an effective solution for the simultaneous monitoring of multiple vital signs.

It is also possible to accurately detect RR under sedentary and ambulatory conditions using a polymer piezoresistive airflow sensor. [46] The sensor showed excellent sensitivity and detection range in experiments. To verify the accuracy of the results, the authors compared the results with the experiments using a laser doppler vibrometer and found that they were highly consistent. This research paves the way for subsequent highly sensitive all-polymer sensors for use in the medical field.

Research on flexible wearable sensors has since received widespread attention and significant developed. Building upon prior achievements, Li et al. [47] developed a multi-modal piezoresistive sensor using cotton fiber as the basic material and polypyrrole (PPy), a polymer with good electrical conductivity, as the conductive material. This sensor was designed for both sound detection and respiratory monitoring. Preliminary testing included movement tracking on a variety of body parts which demonstrated excellence in monitoring weak physiological signals of the human body. Further investigation revealed that the sensor can not only monitor static breathing but also dynamic breathing. As a multi-mode piezoresistive sensor, the CA@PPy sensor provided a new development idea for multi-functional integrated sensors.

This work was further expanded by Y. Li et al. [49] through the development of a degradable and breathable high-performance interdigital piezoresistive sensor. The sensing material of this device was comprised of reduced graphene oxide, silk fiber, and carbon cloth. In experimental tests, it has shown excellent characteristics of high sensitivity, wide response range, fast response, and fast recovery. The author also conducted a series of experiments, placing the sensor on different body positions of the human body such as the wrist and throat to detect its function (Figure 2E). The experimental results showed that the sensor can effectively detect weak physiological signals of the human body, demonstrating that piezoresistive sensors have great prospects for use in wearable sensing monitoring devices.

IV. WEARABLE DEVICES BASED ON OPTICAL FIBERS

Optical fiber sensors detect changes in physical signals (chemical or biological parameters) through variations in light transmitted through optical fibers. They can transmit signals over long distances without causing obvious signal attenuation or loss. Due to their small size, light weight, low power consumption, and easy installation, these sensors are now widely used in the medical field. Additionally, their wide response range and fast response capability make them suitable for dynamic measurement and real-time monitoring. [50-52] Therefore, optical fiber sensors hold significant promise and practical value for long-term monitoring projects.

Specifically, fiber Bragg gratings, a type of optical sensor, are a key component to non-invasive measurement of human physiological parameters using wearable devices. [53-56] Compared to traditional electrical sensors, fiber Bragg gratings are not subject to electromagnetic interference and are not easily corroded. Additionally, as a wavelength-modulated optical fiber sensor, they modulates the fiber Bragg wavelength through external physical parameters to obtain sensing information. [57] Therefore, unlike traditional fiber optical sensors, the accuracy of fiber Bragg grating sensors is unaffected by light source intensity and is less affected by environmental conditions.

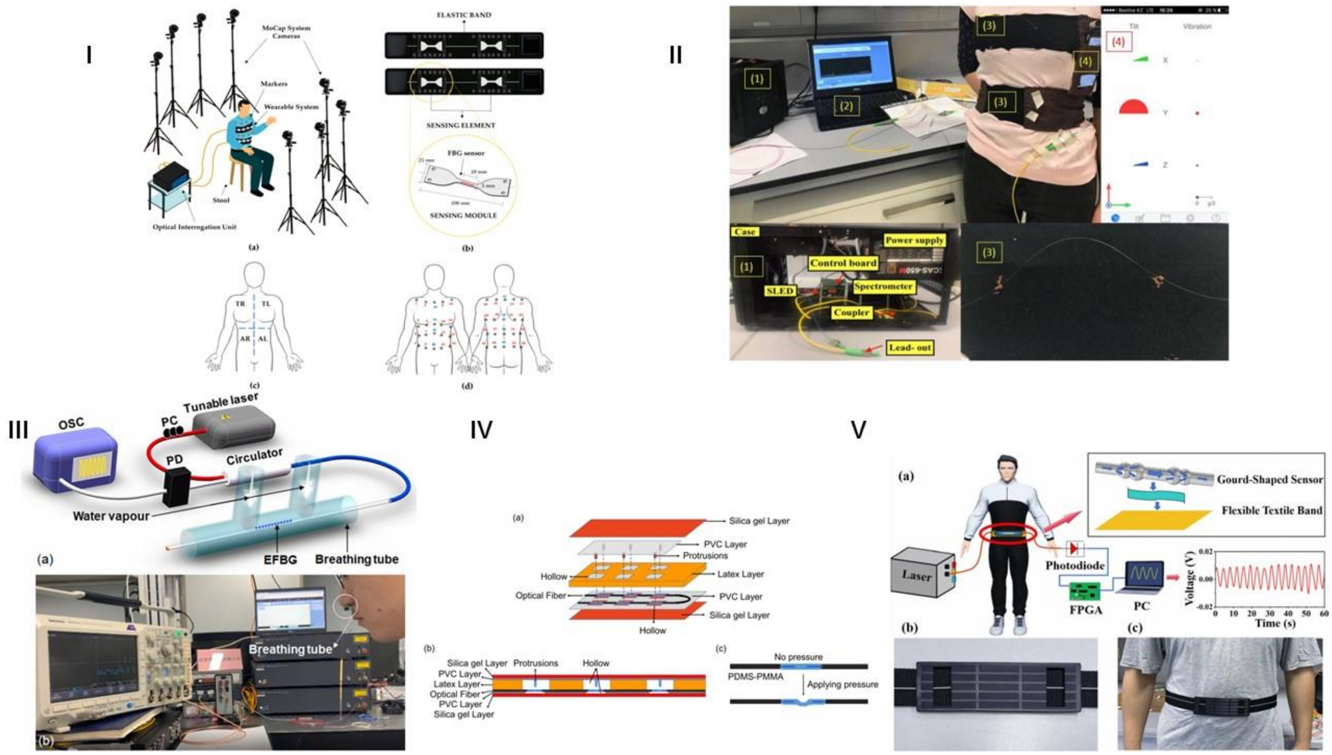

Figure 3. (I) Components of the sensing equipment and illustration of the scene layout [52]. (II) Experimental setup and the appearance of the device [58]. (III) Appearance display of the respiratory device and A volunteer's test process demonstration [59]. (IV) The schematic diagram of the mattress structure [60]. (V) Schematic diagram of the device and the wearing method [61].

Fiber Bragg grating sensors have been used for the detection of RR. [62] In order to ensure the sensitivity of the fiber grating to changes in relative humidity, the sensing element was made of hygroscopic coating material. The study conducted experimental tests on six healthy volunteers to evaluate the feasibility of the device for monitoring. The testers followed the requirement of 10 s of apnea followed by 30 s of slow breathing, normal breathing, and fast breathing respectively. The obtained data were then processed through MATLAB. The signal was first segmented and then filtered through a third-order Butterworth low-pass filter. The cut-off frequency for the data collected by slow breathing and normal breathing is 2 Hz, and the cut-off frequency of the data signal collected by fast breathing is 5 Hz. All signals were then normalized, and finally the normalized signals were peak monitored using a custom algorithm developed by Massaroni et al. [63] The final experimental results showed that the device can monitor slow breathing and normal breathing very well but has a larger error in monitoring fast breathing.

Additionally, a lightweight wearable system composed of 4 flexible sensing modules based on FBG technology was used to monitor respiratory function in patients with hemiplegia. [52] The wearable system uniquely used a modular anchoring system so that it could adapt to any human body habitus or positioning. The device system overlay as shown in the figure 3 (I). The feasibility of the device was evaluated by monitoring normal breathing and rapid breathing in 7 hemiplegic patients demonstrated great performance (error < 6%) in monitoring RR.

Building upon this work, Issatayeva et al. [58] developed an optical fiber-based smart textile product for real time RR detection. From the figure 3 (II), it showed that the system used two elastic bands arrayed with 5 fiber optic grating sensors on the chest and abdomen to monitor the RR. Experiments conducted on volunteers (n=2) under resting and dynamic conditions utilized a specific algorithm to reconstruct breathing patterns. When compared with the commercial VibSensor app, the results showed high accuracy in monitoring respiratory movements. This research advances wearable textile technology for continuous monitoring of biophysiological signals and personalized health management.

Traditional sensing devices based on sensitive materials face significant challenges in maintaining repeatability and consistency. W. Bao et al. [59] proposed a new type of ultrafast response compact optical fiber humidity sensor that did not require the cooperation of other sensitive components to monitor human breathing. The sensor was tested on a volunteer across four breathing modes: normal breathing, deep breathing, fast breathing, and random breathing showed in the figure 3 (III) above. The device was found to achieve high-precision breathing monitoring with the ability to self-compensate for temperature and system power. The eccentric fiber Bragg grating humidity sensor exhibited superior reliability, long-term stability, high sensitivity, fast response, and excellent robustness, indicating its significant potential for wearable devices in monitoring respiratory physiological signals.

Further application of optical fiber sensors includes the use of a stretchable polymer fiber with a sandwich-like structure embedded into mattresses to monitor RR and HR during sleep [60]. The new polymer fiber integrates a silicone tube filled with polydimethylsiloxane and two commercially available polymethylmethacrylate optical fibers. The mattress is made of 5 different layers of materials with the fiber optic sensor located between the latex layer and the PVC layer of the mattress. The middle layer of the mattress has bulges or depressions at specific locations to increase the sensitivity of the mattress to external pressure. To evaluate the feasibility of its sleep monitoring mattress, the author conducted an experimental test on 10 volunteers, allowing them to collect data in different sleeping positions at a sampling frequency of 200 Hz. The collected data were processed through a Butterworth filter to extract respiratory signals and heartbeat signals. Experimental results showed that the maximum absolute errors of respiration and heartbeat are less than once per minute and twice per minute, and the maximum relative errors are 4.1% and 1.6% respectively, which verified the stability and reliability of the device for continuous monitoring.

Lastly, Min Shao et al. [61] proposed a single-mode seven-core optical fiber wearable sensor with a gourd-like structure to monitor human breathing in real time. Seven-core optical fiber (SCF) is composed of a central core and 6 peripheral cores. SCF enhanced the correlation between environment and interference cause its multi-core structure supports multiple supermodel distributions. This breath detection system works on the principle of a change in the intensity of light interference caused by a change in the movement of the abdomen during breathing. The optical signal was converted to an electrical signal, and the resulting electrical signal was amplified and filtered by a Field Programmable Gate Array. Finally, the respiratory signals were collected by computer processing. To test the accuracy and suitability of the wearable device, 11 volunteers were tested for respiratory monitoring. The results of the experiment showed that the sensing device had good mechanical properties, and strong stability without the drift of signal baseline in the respiratory movement in different states of the test. In addition, the sensing device could be flexibly worn on the upper body of the wearer to achieve long-term effective monitoring of human respiration.

V. CHALLENGES AND FUTURE PERSPECTIVES

As wearable devices and communication technologies advance, wearable devices have significantly improved; however, several challenges remain:

A. Power efficiency

As wearable devices become smaller and more portable, space for batteries is reduced. Consequently, modern wearable devices use small-sized batteries, leading to decreased battery capacity and shorter usage time. To achieve long-term use, it is essential to balance the power consumption of each module. Therefore, selecting sensors and central processors that meet low power consumption requirements is crucial.

B. Design and materials

The monitoring and management of certain diseases require patients to wear equipment for extended periods. Therefore, the design of such equipment must adhere to ergonomic principles to prevent discomfort or pressure injury from prolonged use. Additionally, the selection of materials is crucial to ensure safety and avoid skin allergies or irritation. Extended wear can also lead to material abrasion; for instance, continuous pressure on smart textiles can damage the device and compromise data accuracy. Thus, it is essential to explore composite materials that possess high wear resistance, plasticity, and self-recovery capabilities. The journey to enhance the comfort of wearable devices remains a challenging endeavour.

C. Data accuracy

The usability and application of wearable device data is currently limited in integrity by the presence of motion artifacts and incorrect usage. Such erroneous datapoints ultimately impact the accuracy of the diagnostic output. Therefore, more robust algorithms must be generated to mitigate external environmental interference to enable the collection of more robust and accurate data for diagnostic interpretation.

D. Data privacy and security issues

With the increasing prevalence of the Internet of Things (IoT) and the overall digitization of the world, individuals' privacy is at greater risk. Wearable medical devices serve as essential tools for collecting human health data; however, their broader applications and uses are limited by challenges in ensuring data privacy. Wearable devices collect sensitive data about individuals' health assessments and treatments. This data is often used within business blockchains. Based on users' private data, relevant product recommendations or targeted advertisements are pushed to individuals. Furthermore, a more significant threat is the potential exposure of location information and home addresses. If such information is hacked or screened by larger power-brokers or governing entities, it can pose substantial risks to personal safety, property security, or even eligibility for future healthcare or financial services, via social credit systems. [64] Therefore, ensuring the privacy and security of user data is a critical challenge requiring focused resources, guardrails, and policy and engineering constraints.

In general, wearable devices have brought convenience and data opportunities to people's lives in the medical and health field. In the future, the data provided by wearable devices may open doors to greater social benefits and improvements in quality of life, but may also carry risk.

VI. CONCLUSION

Currently, numerous wearable device technologies are employed for remote and continuous monitoring of physiological signals of populations, aiding medical professionals in enhancing healthcare quality and fostering the advancement of novel intelligent, interconnected, and health-conscious medical systems. This article provides a comprehensive review of relevant sensing devices, focusing predominantly on the developmental prospects and significance of wearable devices in monitoring human respiratory signals. The discussion delves into devices utilizing IMU sensors, piezoresistive sensors, and optical fiber sensors, addressing the latest research advancements. Furthermore, persisting shortcomings are examined in current wearable devices designed for monitoring respiratory signals, while also offering insights into future developments. As communication and sensing technologies progress, wearable respiratory sensing device research enters a promising phase, holding significant potential for future medical monitoring and diagnosis, potentially augmented by data informing artificial intelligence pathways and algorithms. Anticipated developments suggest the integration of more sophisticated sensing equipment into daily life, revolutionizing the existing medical infrastructure to make healthy living more preventive, convenient, and automated.

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Table I. Comparison of hardware facilities and service life of sensing equipment.

Reference	Energy storage	Wireless technology	Lifetime (Hours)	Power consumption
[23]	Super capacitors which have 50 F total capacitance and a 5.4 V voltage rate	BLE 2.4 GHz 100 m	46	2.13 mW
[31]	Lithium polymer rechargeable battery (3.7V, 220 mAh)	BLE	8-9	25 mA
[32]	N/A	Bluetooth module	N/A	N/A
[33]	Miniature 100-mA lithium-ion battery	Wi-Fi	6	12-16.2 mA
[34]	These papers do not mention the above data parameters			
[35]				
[36]				
[39]				
[43]	Lithium battery (3.17 V, 150 mAh)	Bluetooth module	3.83	N/A
[44]	N/A	Wi-Fi	N/A	N/A
[45]	N/A	N/A	N/A	N/A
[61]	N/A	N/A	N/A	N/A

Table II. Respiratory monitoring of wearable devices based on Inertial Measurement Unit.

Author	Year	Sensor	Number and size	Sample frequency	Sample size	Application
Cesaero et al.	2017	Inertial measurement unit	3/ 43mm x 28mm x 22mm	N/A	9 testers	Breathing frequency monitoring
Wang et al.	2018	Accelerator, gyroscope, electrocardiogram sensor, temperature sensor	Around 4cm in width and 11 cm in length	N/A	7 testers （5 men, 2 women)	Respiratory rate, heart rate
Elfarmawy et al.	2019	Inertial measurement unit, microphone, wireless patch sensor	26.67mm x 66.53mm	10 kHz	N/A	Wireless respiratory monitoring, Coughing detection
Angelucci & Aliveti	2023	Inertial measurement unit	3	N/A	20 healthy subjects (9 men, 11 women)	Respiratory monitoring
Romano et al.	2023	Inertial measurement unit	36mm x 30mm x 22mm	800 Hz and internally resampled at 120 Hz	15 healthy volunteers	Cardiorespiratory monitoring
Hayano et al.	2024	Inertial measurement unit,	N/A	32 Hz	122 testers	Apnea detection
Zabihi et al.	2024	Accelerometer, resistive pressure sensor	N/A	N/A	6 young adults (3 men, 3 women)	Breathing monitoring

Table III. Respiratory monitoring of wearable devices based on piezoresistive sensor.

Author	Year	Sensor	Number and size	Sample frequency	Sample size	Application
Chu et al.	2019	Strain sensor	21mm x 10mm x 5mm	N/A	8 volunteers	Respiratory rate, respiratory volume
Vanegas et al.	2020	Force-sensitive resistor	73mm x 45mm x 37mm	50 Hz	21 testers (15 men, 16 women)	Respiratory rate
Saha et al.	2020	Piezoresistive sensor	Dimension of length is 15cm; inner diameter is 2.5 cm	1 kHz	2 testers	COPD, asthma, and other respiratory detection and monitoring
Nguyen et al.	2019	Pressure sensor	0.5mm x 1mm x 4cm	N/A	1 tester	Measurement of pulse wave and respiratory rate
Moshizi et al.	2021	Polymeric piezoresistive airflow sensor	7.5mm x 5mm x 2mm	N/A	5 healthy subjects	Respiratory patterns monitoring
J. Li et al.	2023	Piezoresistive sensor	N/A	N/A	N/A	Sound detection, respiratory monitoring
Y. Li et al.	2024	Piezoresistive sensor	N/A	N/A	N/A	Human physiological signals monitoring

Table IV. Respiratory monitoring of wearable devices based on optical fiber sensor.

Author	Year	Sensor	Number and size	Sample frequency	Sample size	Application
Presti et al.	2022	Fiber Bragg grating sensor	N/A	100 Hz	6 healthy volunteers (3 males, 3 females)	Respiratory frequency
Zaltieri et al.	2022	Fiber Bragg grating sensor	N/A	60 Hz	7 hemiplegic patients	Respiratory monitoring
Issatayeva et al.	2020	Fiber Bragg grating sensor	10 FBG sensors/5mm	3000 Hz	2 testers (1 male, 1 female)	Breathing rate
W. Bao et al.	2021	Eccentric fiber Bragg grating	N/A	N/A	N/A	Breath monitoring
L. Li et al.	2024	Stretchable polymer optical fiber	N/A	200 Hz	10 volunteers	Heart rate, respiratory rate
M. Shao et al.	2024	Seven-core fiber	N/A	N/A	11 volunteers (7 males, 4 females)	Respiratory monitoring
Presti et al.	2022	Fiber Bragg grating sensor	N/A	100 Hz	6 healthy volunteers (3 males, 3 females)	Respiratory frequency

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