

Review

Inertial Sensors-Based Assessment of Human Breathing Pattern: A Systematic Literature Review

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Abstract: Breathing pattern assessment holds critical importance in clinical practice for detecting respiratory dysfunctions and their impact on health and wellbeing. This systematic literature review investigates the efficacy of inertial sensors in assessing adult human breathing patterns, exploring various methodologies, challenges, and limitations. Utilizing the PSALSAR framework, incorporating the PICOC method and PRISMA statement for comprehensive research, 22 publications were scrutinized from the Scopus, Web of Science, and PubMed databases. A diverse range of sensor fusion methods, data signal analysis techniques, and classifier performances were investigated. Notably, Madgwick's algorithm and the Principal Component Analysis showed superior performance in tracking respiratory movements. Classifiers like Long Short-Term Memory Recurrent Neural Networks exhibited high accuracy in detecting breathing events. Motion artifacts, limited sample sizes, and physiological variability posed challenges, highlighting the need for further research. Optimal sensor configurations were explored, suggesting improvements with multiple sensors, especially in different body postures. In conclusion, this systematic literature review elucidates methods, challenges, and potential future developments in using inertial sensors for assessing adult human breathing patterns. Overcoming the challenges related to sensor placement, motion artifacts, and algorithm development is essential for progress. Future research should focus on extending sensor applications to clinical settings and diverse populations, enhancing respiratory health management.

Keywords: breathing mobility dysfunction; breathing pattern assessment; inertial sensors; non-intrusive measurement; machine learning classifiers; algorithm; systematic literature review



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1. Introduction

Breathing, an innate and vital biological process, plays a fundamental role in shaping human interactions and activities of daily living. Recognizing and analyzing variations in its pattern has profound clinical significance, offering information about potential respiratory dysfunctions [1–4] and its impact on postural stability [5,6]. Such disorders can lead to musculoskeletal problems, chronic pain, and fatigue, ultimately affecting individuals' interactions with their surroundings, leading to disability [7–11].

In a physiotherapy clinical evaluation setting, the breathing pattern (BP) is typically assessed through a direct observation of chest and abdominal wall motion to gather information about rhythm (respiratory frequency/amplitude ratio), location, and symmetry of motion (right vs. left, chest vs. abdominal), as well as the inspiratory/expiratory (I:E) ratio [5]. However, this evaluation method requires considerable observer expertise and may induce the “Hawthorne Effect” in patients, altering their BP due to the awareness of being observed [12–14].

To complement direct observation, several alternative approaches can be found in the literature. Spirometry, for instance, provides valuable insights into lung volumes, lung capacities, and breathing rhythm but has limitations in assessing chest wall motion and regional contributions [15,16]. Optoelectronic plethysmography, considered the gold standard for biomechanical analysis, offers an accurate measurement of chest wall movements and estimation of lung volumes, but its complexity, time-consuming setups, and the requirement for a large number of infrared camera devices makes it unsuitable for routine clinical use due to its cost and technical demands [17,18].

CT scans and X-rays offer high precision but are costly and not suitable for real-time assessment [19–21]. Depth camera devices allow for the observation of chest displacement, but like optoelectronic devices, relevant data collection depends on the subjects being within the camera's view angle, and data acquisition quality is influenced by ambient lighting conditions [22–25].

Radar devices are also reported as good non-intrusive alternatives for assessing BP, but the technologies available for medical devices have limitations. They require high power energy to transmit a short pulse period signal [26] and face issues with measuring tiny positional changes and signal interference from other moving objects around the subjects [27]. Additionally, their signal acquisition depends on the distance between the subjects and the radar, limiting their use to specific locations. They also cannot differentiate between right vs. left chest wall motion asymmetries [26,28–31].

Similarly, Wi-Fi-based devices offer convenient assessment of breathing rhythm but lack the ability to differentiate between right vs. left chest motion, upper vs. lower chest, and chest vs. abdominal motion [32–34]. Inductive respiratory plethysmography provides a non-intrusive option for assessing BP but also lacks the ability to differentiate chest wall right vs. left motion asymmetries [35]. Measuring tape, despite its reported high reliability in chest mobility measurements, shows wide variability in measurements between observers (2.03–4.29 cm) [36,37]. Palpation evaluates the mobility of the chest and abdomen by using bare hands to feel and quantify the amount of movement in the area under assessment, which can significantly induce changes in the patient's actual BP [38,39].

Despite the advantages of all the alternatives mentioned above, their limitations make them less suitable for a clinical physiotherapy setting as they lack the ability to simultaneously evaluate all mentioned variables with optimal cost-effectiveness and time efficiency. Moreover, they are not suitable for the real-time monitoring of BP in patients' daily living activities and social interaction contexts without signal acquisition constraints.

On the other hand, inertial measurement units (IMUs), similar to Optoelectronic Plethysmography, are also a reference for biomechanical analysis, having a very good accuracy [40] but without the constraints imposed by the infrared or depth cameras. Their compact size enables independent measurement of both sides of the chest wall, providing valuable information about motion asymmetries. Additionally, due to their small size, these devices can measure human movement in real time and in a way that is nearly imperceptible to the users. They are easily deployable, capable of collecting vast amounts of data, and can be seamlessly integrated into real-world scenarios.

The purpose of this systematic literature review (SLR) is to investigate how inertial sensors can be employed more effectively in assessing the adult human BP, considering the variety of available quantification, classification, and mapping methods, as well as the associated challenges and limitations, with the aim of improving the detection and diagnosis of respiratory disorders.

2. Methodology

According to Mengist et al. [41], conducting an SLR allows us to gather relevant evidence related to a particular subject of interest and effectively address research questions. The fundamental purpose of an SLR is to compile existing research, studies, and publications that meet pre-defined inclusion criteria and provide insights into a specific research question. Grant and Booth [42] have suggested the SALSA framework for conducting

SLRs, which emphasizes the reproducibility, systematization, methodological accuracy, and comprehensiveness of the study. Building upon the work of Mengist et al. [41], the SALSA framework is expanded by incorporating the preferred reporting items for systematic review and meta-analyses (PRISMA) statement into the PSALSAR (protocol, search, appraisal, synthesis, analysis, and report) research process, further enhancing its scope. A summary of the PSALSAR framework utilized in the study can be found in Table 1. A detailed explanation of each step and their corresponding outcomes are explained in the following subsections.

Table 1. Protocol and Reporting result with Search, Appraisal, Synthesis, and Analysis (PSALSAR) framework used in the study.

	Steps	Outcomes	Methods
PSALSAR Framework	Protocol	Define study scope	PICOC (Population, Intervention, Comparison, Outcome, and Context) framework.
	Search	Define the search strategy Search studies	Searching strings Search databases
	Appraisal	Selecting studies Quality assessment of studies	Defining inclusion and exclusion criteria Quality criteria
	Synthesis	Extract data Categorize the data	Extraction template Categorize the data on the iterative definition and ready it for further analysis work
	Analysis	Data analysis Result and discussion	Qualitative categories, description, and narrative analysis of the organized data Identify emerging trends, pinpoint existing gaps, and provide comparative evaluation of the results.
	Report	Conclusion Report writing	Deriving conclusion and recommendation Summarizing the results using PRISMA methodology

2.1. Protocol Establishment and Study Scope

According to Booth et al. [43], the incorporation of the PICOC method at each stage of the PSALSAR framework ensures transparency and transferability of the study by providing a prescribed structure to decompose research questions and improve the definition of the research scope. The PICOC framework together with the definition of each concept is listed in Table 2.

Given that the primary research question revolves around the effectiveness of inertial sensors in assessing the BP of adult humans, while taking into account the strengths and limitations of various methods employed for quantifying, evaluating, and mapping changes in BP, the following sub-questions were formulated:

- (1) What methods are being employed to enhance IMU-based adult human BP assessment?
- (2) Which classifiers are being employed and best perform detecting adult human BP?
- (3) How reliable are IMUs in identifying signals associated with adult human BP?
- (4) Is there an ideal number of sensors and configurations to accurately assess adult human BP?
- (5) What are the main challenges and limitations when using inertial sensors in assessing adult human BP?
- (6) What insights have been gained, and what future directions are envisioned for applying inertial sensors in the assessment of adult human BP?

Table 2. PICOC Framework (Population, Intervention, Comparison, Outcome, and Context).

Concept	Definition According to Booth et al. [43]	SLR Application
Population	The research focuses on the assessment of adult human breathing patterns using inertial sensors.	Scientific research work on adult human breathing patterns assessment. Focused on the use of inertial sensors, their strengths, and weaknesses.
Intervention	Existing techniques and methods to address the problem.	The use of inertial sensors methods and techniques utilized to address adult human BP assessment to identify gaps in current methods, protocols, and device setups.
Comparison	Techniques to contrast the intervention used to measure the BP.	The difference between different methods applied to quantify/value/map adult human BP.
Outcomes	Measure to assess the knowledge and gaps mentioned in the selected publications regarding the assessment of adult human BP using inertial sensors.	Existing knowledge on the assessment of adult human BP using inertial sensors, such as methods and techniques approach used, data types, and purpose. Mentioned gaps: limitations related to applied methods and techniques and data quality.
Context	The particular settings or areas of the population.	Research trends in adult human breathing patterns, existing knowledge in studies of adult human breathing patterns, and the challenges and gaps in adult human breathing patterns measurement.

2.2. Search Strategy

Three databases—Scopus, Web of Science (WoS), and PubMed—were selected for the conventional subject search based on the nature of the study topic area. Scopus is an abstract and indexing database developed by Elsevier Co. It claims to be the largest single abstract and indexing database ever built, indexing over 14,000 STM and social science titles from 4000 publishers. With 4600 health science titles, including complete coverage of MEDLINE, EMBASE, and Compendex, its vast repository comprises 27 million abstracts dating back to 1966, and it encompasses not only American journals but also papers from Europe and the Asia Pacific region, published in various languages, including English [44]. WoS is the world’s oldest, most widely used, and authoritative database of research publications and citations, and it was established in 1964 by Eugene Garfield; its Core Collection database, based on the Science Citation Index, is a selective citation index that includes scientific and scholarly publications such as journals, proceedings, books, and data compilations [45]. PubMed is a free online research database for the health sciences maintained by the National Center for Biotechnology Information (NCBI) at the U.S. National Library of Medicine (NLM), which is part of the National Institutes of Health (NIH). Widely used by healthcare researchers, practitioners, and students around the globe, it contains over 35 million citations and abstracts of biomedical literature and offers links to full-text articles [46,47].

The full search string definition for this study was derived from the terminology identified for the target population within the framework of the SLR using the PICOC framework (Table 2) and primarily focuses on the assessment of adult human BP using inertial wearable sensors.

The search strategy was conducted until 4 May 2023 and involved leveraging the advanced search features of each database, employing two distinct search strings that targeted specific keywords in the titles and abstracts of the references. The main search string included the terms “breathing pattern”, “respiration pattern”, or “respiratory pattern” combined with “assessment”, “evaluation”, or “analysis” and was further combined with “wearable”, “inertial sensor”, or “accelerometer”. On the other hand, the secondary search string encompassed “rib cage motion”, “chest wall motion”, “chest motion”, “rib cage mobility”, “chest wall mobility”, or “chest mobility” coupled with “assessment”, “evaluation”, or “analysis” and was further combined with “wearable”, “inertial sensor”, or “accelerometer”.

To refine the results, exclusion keywords were implemented. These keywords aimed to filter out references related to “children”, “infant”, “child”, “baby”, “newborn”, “newborns”, “animal”, “rat”, “rats”, “rabbit”, “rabbits”, “monkey”, “monkeys”, “dog”, “dogs”, “cat”, “cats”, “fracture”, “trauma”, “injury”, “injuries”, “lesion”, or “lesions”. Additionally, a language filter was applied, limiting the search results to English, French, Portuguese, or Spanish.

Combining all of these parameters yielded a total of 30 publications in Scopus, 51 in WoS, and 40 in PubMed.

Additional details of the search strategy are provided in Table S1 (Supplementary Material), allowing the search to be reproduced and updated.

2.3. Studies Selection and Quality Assessment

Upon completion of the database search, the search results were exported and compiled in Zotero version 6.0.26. This enabled efficient management of duplicate references and facilitated subsequent readings to apply the inclusion and exclusion criteria, as presented in Table 3, for further investigation and content assessment.

Table 3. SRL study selection of literature inclusion and exclusion criteria.

Criteria	Decision
Predefined keywords must be found in the full text or at least in the title or abstract section of the papers.	Inclusion
Papers must be published in a scientific peer-reviewed journal.	Inclusion
Papers should be written in English, French, Portuguese, or Spanish.	Inclusion
Papers presenting evidence on the use of inertial sensors for BP assessment.	Inclusion
Papers must address at least one of the BP outcome features.	Inclusion
Predefined exclusion keywords are found in the full text or at least in the title or abstract section of the papers.	Exclusion
Papers that are duplicated within the search results.	Exclusion
Papers that are not accessible, review papers, and meta-data.	Exclusion
Papers that are not primary/original research.	Exclusion

The process of selecting relevant literature involved a general screening process and information flow, as depicted in Figure 1.

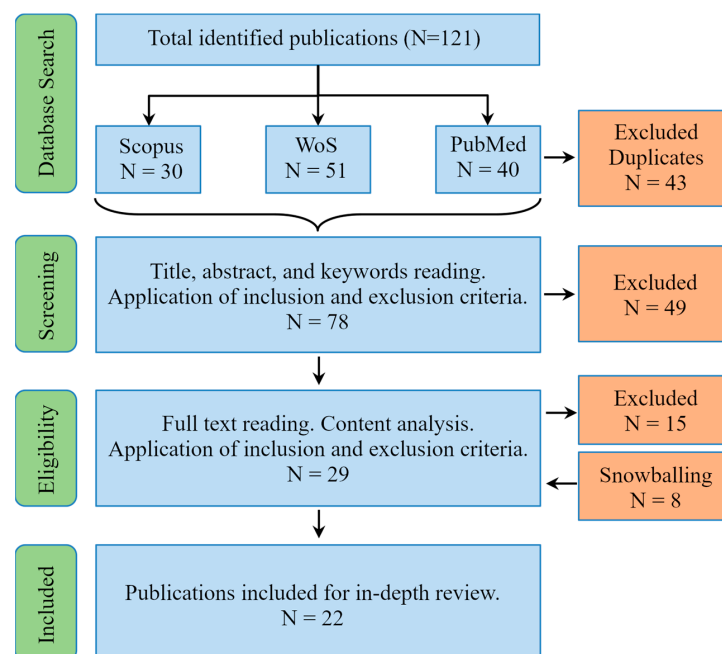


Figure 1. General screening process and information flow for SLR-relevant literature selection. N = number of publications.

After merging the results from each database and removing duplicates, a total of 78 publications were identified. These publications were then subjected to a primary selection process based on the evaluation of their titles and abstracts while applying the inclusion and exclusion criteria. Through this initial screening, 29 publications were deemed eligible for further consideration.

These 29 publications underwent a secondary selection process led by two of the authors (R.M. and N.C.). This process involved a thorough review of the full texts using a snowballing technique while also applying the predefined inclusion and exclusion criteria. The reviewer authors worked simultaneously and in parallel to ensure a consensus-based final decision. Following this thorough evaluation, 22 publications were chosen for inclusion in the final systematic literature review (SLR) to undergo an in-depth analysis. The selection and assessment of publications were based on their alignment with the objectives of the SLR.

2.4. Data Extraction and Categorization

In this step, the two authors involved in the eligibility step applied the 6 research sub-questions to curate and extract relevant data from the in-depth review of the included publications. Subsequently, the extracted information was sorted and grouped according to the criteria outlined in the Supplementary Materials (refer to Tables S2 and S3). The following subsections elaborate on this process of organization and characterization.

2.4.1. Population and Age

Eleven studies presented the ages of the participants in time intervals, varying between 18 and 67 years of age [48–58]. Four studies covered the age by reporting only the global mean, varying between $\bar{x} = 23$ and $\bar{x} = 29.16$ [59–62]. One study reported the mean age by severity of condition ($\bar{x} = 30.0$ to $\bar{x} = 50.3$ [63]), and another study discriminated the mean age by sex ($\bar{x}_{\text{♀}} = 37$ and $\bar{x}_{\text{♂}} = 33$ [64]). In 5 studies, the age of participants was not reported [65–69]. The population in studies was most often males. Three studies included only male participants [53,58,62]. Fourteen studies had both males and female participants [48–52,54–57,60,61,63,64,66], one study included a non-binary participant [60], and in five studies, the gender was not reported [59,65,67–69].

The population was mostly healthy without complaints of any relevant respiratory or cardiac disorder, as reported by fourteen studies [48–50,52,54–59,61,64–66]. Among the remaining eight studies, one focused solely on participants without neurological changes [53], another on those without medication usage [62], and one on participants with suspected sleep apnea disorders [63], and in five studies, the specific condition was not reported [51,60,67–69].

2.4.2. Devices and Sensor Setup

A total of 26 different types of devices were used to analyze BP. The most common manufacturer was STMicroelectronics International N.V., Amsterdam, The Netherlands, with devices used in five studies [50–52,59,66], followed by NXP Semiconductors N.V., Eindhoven, The Netherlands, with devices used in four studies [54,61,62,65]; Analog Devices, Inc., Norwood, MA, USA, with devices used in four studies [49,58,62,65]; InvenSense, Inc., San Jose, CA, USA, with devices used in three studies [62,63,68]; and SparkFun Electronics, Niwot, CO, USA, with devices used in two studies [60,67]. Other manufacturers were referenced with devices used only in one study each: a Delsys Trigno™ [48], LG Nexus 5 [69], MC10, Inc./Medidata BioStamp nPoint® [55], Biocubica Srl Soundi [56], ZurichMOVE 9-axis IMU [57], Honeywell HMC1052 dual-axis magnetometer [65], Xsens/Movella MT9-B IMU [53], and BioPac Systems strain gauge transducer [49]. In 1 study, only the sensor type was reported, omitting the manufacturer or device [64], and in 12 studies, the authors had combined more than one sensor to collect and analyze BP data [49,53,55,56,59,60,62–65,67,69]. The sampling rates varied from 10 Hz to 2000 Hz with the most common frequencies, 50 Hz and 100 Hz, being used in 9 studies [50–52,56,57,61,63,67,69].

The location and number of devices also showed variations (Figure 2).

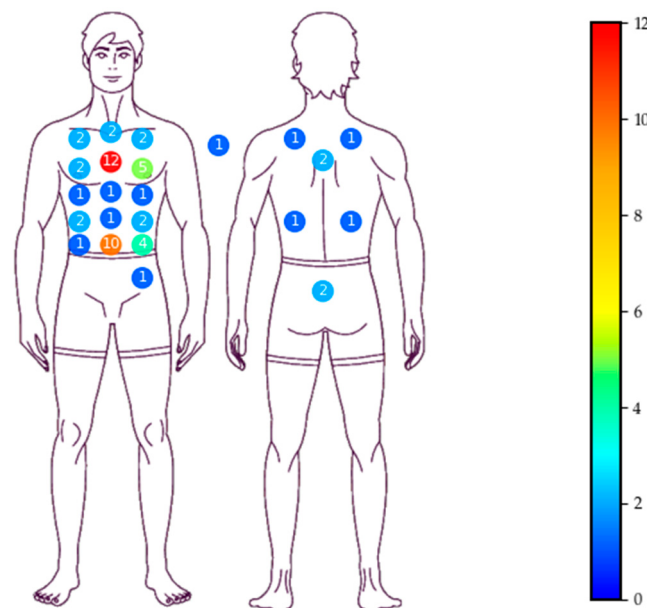


Figure 2. Body locations of sensor attachment and number of articles referring to each location. The number in each circle is the total number of articles that mention placing a sensor in that location. Referring to the body chart in the figure: Anterior view, from top to bottom, right to left of the body chart: right 2nd–3rd rib, manubrium, left 2nd–3rd rib, right 4th–5th rib, body of sternum, left 4th–5th rib, right 7th rib, xiphoid, left 7th rib, right 10th rib, bellow xiphoid, left 10th rib, bellow right ribs, abdominal region, bellow left ribs, and anterior superior iliac spine; Posterior view, from top to bottom, left to right of the body chart: left 2nd–3rd rib, thoracic intervertebrae (T4–T5), right 2nd–3rd rib, left 10th rib, right 10th rib, and sacrum. The only circle outside the body chart is referred to as the body region not related to respiratory movements or a stationary object, as are the sensors found in the anterior superior iliac spine and the sacrum. This figure has been designed using assets from www.freepik.com (accessed on 30 April 2024).

While there are three distinct anatomical regions mentioned—the anterior and posterior regions of the thorax, as well as the abdomen—the precise placement of the devices differs within each of these regions. The anterior region of the thorax was the most reported, being present in 14 studies, of which 6 mentioned the ribs as the fixation site (e.g., 2nd, 4th, 5th, 7th, 10th, precordial region [48,54,56,58,62,63]), and of which 9 mentioned the sternum (e.g., body of the sternum, suprasternal notch, manubrium, above xiphoid process [49–52,57,58,61,68,69]). The abdominal region was reported in 10 studies (e.g., bellow the ribs, linea alba, umbilical region [48,50,52,55,58,59,61,63,64,66]), and the posterior region of the thorax was reported in only 2 studies (e.g., T2, T4, T5, T10 [48,68]). There were also 5 studies that did not specify an exact location, indicating only the thorax or chest for the fixation of the devices [55,59,60,64,66]; furthermore, 2 studies indicated a body region not related to respiratory movements or a stationary object [59,66]. The number of devices used ranged from 1 to 14, with 1 being the most commonly used total of devices reported in 11 studies [49,51,53,56,57,60–62,65,67,69].

2.4.3. Measured BP Metrics

A wide variety of different types of devices led to different combinations of sensors used. A total of 13 studies used measurements from accelerometers only [48–52,54,56–58,61,63,67,69]. Five studies used measurements from accelerometers and gyroscopes [55, 59,62,64,65]. Four studies used measurements from accelerometers, gyroscopes, and magnetometers [53,60,66,68].

In 19 studies, a reference device was used for data comparison [48–54,57–63,65–69]. Among the reference devices, the spirometer was the most frequently employed, appearing in nine studies [48–54,67,68]. Other reported reference devices encompassed stretch sensors like piezo-electric bands [60,62,63], optoelectronic plethysmography [59,66], polysomnography [57,63,64], pressure sensors and strain gauge respirometry [49,61], pneumotachograph [58], air flow pressure transducer [65], and ergospirometry [48].

In three studies, the use of reference devices was not clearly indicated [55,56,64], and one study utilized signal bank data [69].

2.4.4. Experimental Task Performed

As expected, all 22 selected studies referred to the breathing activity as the primary experimental task used to measure BP metrics. This was carried out either through simulated and guided methods (such as mimicking yawns, coughs, or sighs and adjusting breath speed or volume) or in a more natural and spontaneous manner. Nevertheless, a subset of studies specified the measurement of breathing in a particular posture [48,53,59,61,65,68], alternating between different postures [49,50,56,58,66,67], and during sleep [57,63,69], physical activity [62], and speech [53].

2.4.5. Methods Employed for Data Processing

Generally, the approaches used in data processing across the studies follow similar strategies. The process typically starts with sensor alignment and data fusion. Subsequently, filtering techniques and smoothing methods are applied, along with dimensionality reduction and other signal processing techniques, facilitating the selection and extraction of pertinent features. This culminates in the final step of pattern classification. Despite this shared framework, the specific methods employed do vary among the studies.

In the domain of aligning sensors and data fusion, several approaches have been adopted. Some studies utilized the Kalman filter [62,66] and MARG (Magnetic, Angular Rate, and Gravity) systems [59,66], while others employed Madgwick's algorithm [59,60,66]. Additionally, the least squares method was used from six stationary positions [50,52], and there was also the rotation of sensors' reference systems [54].

For filtering and smoothing methods, a range of techniques have been employed, including Type-II Chebyshev low-pass filter [67], Butterworth high-pass or low-pass filter [48,49,52,56,60–62,69], Infinite Impulse Response Butterworth high-pass or low-pass filter [51,53,57,59], Finite Impulse Response filter [50,51,54], Savitzky–Golay smoothing filter [62], and moving average [48,59,60].

Dimensionality reduction and other signal processing techniques include Power Spectral Density [66], Principal Component Analysis [48,65,66,69], and covariance matrix analysis [48]. Additionally, Symbolic Aggregate Approximation [52], Synchrosqueezing Transform [63], Hilbert Transformation, and Fourier Transformation [67] have been employed, along with methods such as Fixed-size Nonoverlapping Sliding Window and Fixed-size Overlapping Sliding Window [52]. Independent Component Analysis has been utilized as well [58], and phase shift determination has been applied using techniques like peak and troughs detection algorithms [51,57,59–63,65–67] and Lissajous figures or the Konno–Mead loop method [50,52,53].

Several studies have outlined their methodologies for pattern classification. These encompass a diverse range of techniques, including Modified Long Short-Term Memory Recurrent Neural Network [63], K-means clustering [48], Correlation-based Feature Selection, Decision Tree, Decision Tree Bagging, Linear Discriminant Analysis, k-Nearest Neighbors, Support Vector Machines, Multilayer Artificial Neural Networks [52], One-dimensional Convolutional Neural Network [55,56,64], Markov chain Monte Carlo [60], and Wavelet Cross-Spectrum analysis [62]. Furthermore, certain researchers have developed proprietary models [57], while others have employed alternative graphical methods, such as the Bland–Altman plot [61], to assess the level of agreement or disagreement between sensors and reference data.

2.4.6. Findings

Regarding the compiled results, they can be categorized based on the effectiveness of sensor fusion methods and data signal analysis techniques, the performance of classifiers for detecting BP, the reliability in identifying signal events, the optimal number of sensors and setup, the impact of changing position and body dynamics on data acquisition, and the challenges and limitations encountered in the studies.

In the realm of sensor fusion methods and data signal analysis techniques, several noteworthy findings emerged from various studies. Cesareo et al. [66] highlighted the superiority of Madgwick's algorithm over Kalman-based methods, even at low sampling rates, due to its accuracy and low computational load along with its ability to compensate for magnetic distortion and gyroscope bias drift. Additionally, they found that the Principal Component Analysis (PCA) fusion method exhibited optimal performance by selecting the most suitable quaternion component based on Power Spectral Density (PSD) analysis. Yoon et al. [62] emphasized that fusion methods outperformed single accelerometers, reducing error rates from 11.9% to 7.3%. They achieved this improvement by employing a Kalman filter to mitigate gyro sensor drift, enabling precise respiration tracking during physical activity. Fekr et al. [51] conducted a window size analysis, revealing that larger window sizes yielded better accelerometer–spirometer correlation by eliminating unwanted rib cage motion. Smaller window sizes resulted in increased standard deviation, impacting Mean Square Error (MSE) distributions. The choice of window size depended on the characteristics of breathing disorders.

In the evaluation of classifiers' performance in detecting BP, several studies offered valuable insights. Chang et al. [63] demonstrated that Long Short-Term Memory Recurrent Neural Networks (LSTM-RNNs) outperformed generic Support Vector Machines (SVMs) with an F1 score of 71% compared with 65%. LSTM-RNNs also exhibited smaller differences in Apnea–Hypopnea Index (AHI) and achieved high accuracy in severity classification. De la Fuente et al. [48] introduced an approach that effectively recognized breathing movements compared with other methods employing reflective markers or kinematics. Fekr et al. [52] reported impressive results with SVM and two sensors, achieving 97.50% accuracy using all features for breathing dysfunction classification, even surpassing 99% accuracy in distinguishing healthy individuals. McClure et al. [55] and Rubavathy et al. [64] both presented classification results, including 95% accuracy in detecting Central Sleep Apnea and 86% accuracy in detecting Obstructive Sleep Apnea, with F1 scores ranging from 52% to 95% for various events in multi-event classification. Rossi et al. [56] leveraged Neural Networks to achieve classification accuracies ranging from 61% to 97% across different breathing conditions, while Ryser et al. [57] reported classification results aligning with clinical standards, achieving a 70.95% accuracy in detecting disrupted respiratory events and a mean sensitivity of 76.05% while using a simple setup.

In assessing the reliability of identifying signal events related to BP, several studies provided valuable findings. Chang et al. [63] highlighted the challenges in identifying Hypopnea (HYP) events while successfully identifying Normal Obstructive Respiratory (NOR) and Obstructive Sleep Apnea (OSA) events, achieving an accuracy of 92.3% in distinguishing abnormal events. Das et al. [67] emphasized the importance of multisensor patches as they improved event detection reliability by complementing each other's flaws, utilizing various sensors like accelerometers and pressure sensors. Guul et al. [69] showcased the capability of detecting breath rates and identifying apnea events using accelerometer data and audio features, calculating the AHI and achieving variance values of 0.5 for heart rate and 0.87 for respiratory rate. Lapi et al. [54] successfully detected respiratory frequency and amplitude with accelerometer data, distinguishing various BPs and coughs qualitatively. Bates et al. [65] reported strong correlations between angular rate output and cannula pressure data, minimizing Root Mean Square (RMS) error in respiratory rate estimation, enhancing signal event reliability. Cesareo et al. [59] indicated a strong correlation and agreement between device and Optoelectronic Plethysmography (OEP) breathing frequency measurements, especially within the healthy adult resting range, while

noting errors at higher breathing frequencies. Gollee and Chen [53] explored IMUs and spirometry signals, highlighting their capabilities in identifying expiration and inspiration onsets and phase shifts during BPs, though potential errors in IMU signal alignment during specific activities were noted. Dehkordi et al. [49] demonstrated the advantages of Acceleration-Derived Respiratory (ADR) measurements over Strain Gauge Spirometry (SGR) belts, particularly in accuracy and robustness across positions and breathing conditions. Fekr et al. [50,51] reported strong correlations between accelerometer and spirometer signals, with generally low MSE values affirming their reliability in capturing respiratory patterns. Preejith et al. [61] highlighted a wearable device's accuracy in measuring respiratory rate, even during minimal movements, effectively eliminating motion artifacts and enhancing signal event reliability.

By exploring the optimal number of sensors and setup configurations, several studies yielded valuable findings. De la Fuente et al. [48] demonstrated that accelerometers localized on the upper chest were effective in detecting the costal-superior pattern, while accelerometers placed on the lower chest and abdominal wall detected the costal-abdominal pattern. Gaidhani et al. [68] introduced a breath detection method utilizing information from two different IMUs placed on the anterior and posterior sides of the chest, suggesting that incorporating one more IMU on the abdomen could enhance breath activity evaluation. Siqueira et al. [58] found that the quality of estimation significantly improved with up to eight accelerometers, with no notable enhancement in estimation quality observed beyond eight sensors, often finding right-hand accelerometers providing the optimal Minimum Mean Square Error (MMSE) estimate in various body postures. Bates et al. [65] noted that combining accelerometer and magnetometer data had the potential to improve accuracy but came at the cost of increased power usage and device cost.

The impact of changing position and body dynamics on data acquisition was explored in several studies, yielding noteworthy results. Cesareo et al. [66] observed enhanced performance in the supine position compared with the seated position, possibly due to reduced trunk oscillations in the absence of back support during seating. Das et al. [67] highlighted the potential for motion artifacts resulting from subject movement, sensor patch disturbance, friction, and slippage. De la Fuente et al. [48] discovered regional differences in tidal breath patterns in the seated position, suggesting the feasibility of measuring such differences using accelerometers. Frey et al. [60] found that the device's sensing capability was unreliable during walking, indicating limitations in capturing data during dynamic activities. Lapi et al. [54] successfully captured postural behaviors during sleep using long-term accelerometric recordings in normal subjects. Dehkordi et al. [49] demonstrated that ADR measurements provided superior results for the relative error of breath rates across different positions. Fekr et al. [50] noted that body position influenced correlation and time variables but maintained a mean correlation above 0.8 across positions and BPs. Preejith et al. [61] reported that the device's accuracy in measuring respiratory rate remained satisfactory during minimal movements, with their proposed solution effectively eliminating motion artifacts.

Finally, to acknowledge the challenges and limitations encountered in these studies, De la Fuente et al. [48] pointed out challenges in the physiological distribution of sensors and the need for advanced data analysis algorithms, particularly in different populations. Frey et al. [60] and Gaidhani et al. [68] highlighted the limitation of small sample sizes in their studies. Lapi et al. [54] recognized interference from body motion as a limitation, although it was considered valuable for clinical use. McClure et al. [55] emphasized the challenges in identifying key data features influencing decisions in deep learning applications and the need for better CNN training with data from actual sleep apnea patients. Rossi et al. [56] cautioned that their results might not be extrapolated to a broader population of individuals with sleep disorders due to the lack of data on pathological sleep conditions. Ryser et al. [57] acknowledged limitations in their classification model's ability to distinguish between central and obstructive apnea/hypopnea, likely due to a small dataset of healthy subjects. Siqueira et al. [58] highlighted the need to explore the

effects of respiratory pathologies, as their study involved only healthy male participants. Bates et al. [65] noted that lower movement detection thresholds increased sensitivity to movement but could potentially discard valid data. Cesareo et al. [59] recognized errors at higher breathing frequencies and data loss rates in their sensor units under various conditions. Gollee and Chen [53] pointed out the potential effects of high-pass filtering on IMU signal alignment and suggested combining signals from multiple IMU sensors to improve reliability. Dehkordi et al. [49] discussed the susceptibility of ADR to motion artifacts and the limitations of SGR in terms of belt placement and tension. Preejith et al. [61] identified challenges related to false positives and false negatives in cycle detection, influenced by motion-induced corruptions and sensor placement issues.

3. Data Analysis, Results, and Discussion

This SLR focuses on researching the methods utilized, comparing their similarities and differences, quantifying variables and kinematic parameters, addressing limitations and challenges, and exploring future directions within the field of adult human BP assessment using inertial sensors. In this section, we discuss the key findings and implications in relation to the research questions.

3.1. What Methods Are Being Employed to Enhance IMU-Based Adult Human BP Assessment?

Various sensor fusion methods and data signal analysis techniques have been employed in studies focusing on inertial sensors for measuring BPs. These methods have contributed to improving the accuracy and reliability of detecting and quantifying BPs. Notably, Madgwick's algorithm was found to be superior in some studies, offering high accuracy and low computational load, while the Principal Component Analysis (PCA) fusion method demonstrated optimal performance in selecting relevant features. These findings suggest that the choice of sensor fusion method and data analysis technique can significantly impact the effectiveness of inertial sensors in assessing BPs. Researchers should carefully consider these factors when designing experiments and data processing pipelines.

3.2. Which Classifiers Are Being Employed and Perform Best in Detecting Adult Human BPs?

A wide range of classification techniques have been employed to detect and classify BPs using inertial sensors. Long Short-Term Memory Recurrent Neural Networks (LSTM-RNNs) showed promise in achieving high accuracy, especially in classifying the severity of breathing disorders. Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) have also demonstrated strong performance in various studies. These findings suggest that machine learning approaches can be effective in automating the detection and classification of BPs based on inertial sensor data. However, it is essential to choose the appropriate classifier based on the specific research objectives and data characteristics.

3.3. How Reliable Are IMUs at Identifying Signals Associated with Adult Human BPs?

Inertial sensors proved to be capable of detecting breath rates, apnea events, respiratory frequency, and amplitude, even in different body positions and conditions. Additionally, accelerometer data showed strong correlations with other reference devices, such as spirometers and pressure sensors, enhancing signal event reliability. These findings suggest that inertial sensors can provide reliable measurements of breathing-related signal events, making them valuable tools for respiratory assessment in various scenarios.

3.4. Is There an Ideal Number of Sensors and Configurations to Accurately Assess Adult Human BPs?

This review provided insights into the optimal number of sensors and setup configurations for assessing BPs. Studies showed that accelerometers placed on different anatomical regions, such as the upper chest, lower chest, and abdominal wall, were effective at detecting specific BPs. Furthermore, the use of multiple sensors, including accelerometers,

gyroscopes, and magnetometers, was common in the research, enhancing the robustness of data collection and analysis. These findings suggest that the choice of sensor placement and the use of multiple sensors can be tailored to specific research objectives and the desired level of accuracy.

3.5. What Are the Main Challenges and Limitations When Using Inertial Sensors in Assessing Adult Human BPs?

Several studies have investigated the impact of changing body positions and dynamics on data acquisition using inertial sensors, revealing the versatility of these sensors in capturing BPs across various contexts. While most research has focused on measuring BPs at rest, some have explored scenarios involving physical activity, speech, and sleep, demonstrating the potential of inertial sensors. However, these studies have also highlighted challenges related to sensor alignment and potential errors during specific activities, which researchers need to consider when designing experiments in dynamic settings. This review has also underscored several challenges and limitations associated with using inertial sensors for assessing BPs, including issues with sensor accuracy, potential errors during sensor alignment, and difficulties in identifying specific events like hypopnea. Furthermore, variations in sensor types and sampling rates observed across studies have emphasized the importance of standardizing approaches in future research. These findings emphasize the need to address these challenges and limitations to improve the reliability and accuracy of inertial sensor-based assessments of BPs.

3.6. What Insights Have Been Gained, and What Future Directions Are Envisioned for Applying Inertial Sensors in the Assessment of Adult Human BP?

Based on the findings of this review, several future directions can be envisioned for applying inertial sensors in the detection of adult human BPs. Researchers should continue to explore advanced sensor fusion methods and data signal analysis techniques to enhance the accuracy and reliability of BP assessments. Additionally, the development of robust classifiers tailored to specific clinical applications should be a focus of future research. Standardization of sensor placement and data collection protocols can help reduce variability and improve comparability across studies. Moreover, investigating the feasibility of the real-time monitoring of BPs using wearable inertial sensors holds promise for clinical applications and the early detection of respiratory disorders.

However, despite the valuable insights gained from this systematic literature review, it is important to acknowledge and address several limitations inherent in the methodology and scope of the study. Because the study is a systematic literature review rather than a true systematic review, the authors chose not to assess certainty, considering one of the inclusion criteria being papers published in scientific peer-reviewed journals. Additionally, this review took a descriptive approach to provide a comprehensive overview of the literature. Due to the specific inclusion/exclusion criteria focusing on particular aspects of the research topic, the authors did not formally assess the risk of bias for included studies. While a formal analysis of result strength was not performed, all compiled information was based on the authors' six specific research questions.

4. Conclusions

This SLR has provided comprehensive insights into the field of detecting and monitoring BP using sensor technologies. Key findings across various aspects, including sensor fusion methods, classifier performance, the reliability of signal event identification, optimal sensor setups, and the impact of changing body dynamics, have been synthesized.

Sensor fusion methods and data signal analysis techniques have shown promising results, with Madgwick's algorithm emerging as a standout method due to its accuracy, low computational load, and ability to compensate for distortions [66]. Fusion methods have generally outperformed single accelerometers, improving accuracy and reducing error rates [62].

Classifiers, particularly Long Short-Term Memory Recurrent Neural Networks (LSTM-RNNs) and Support Vector Machines (SVMs), have demonstrated high accuracy in detecting breathing disorders, with potential for enhancing diagnostic accuracy and treatment efficacy [52,63].

Reliability in identifying signal events related to BP has been confirmed, with multisensor patches and strong correlations between sensor signals enhancing event detection [67,69]. However, challenges such as motion artifacts and sensor placement issues persist [61].

Optimal sensor setups have been explored, suggesting effective configurations for detecting breathing patterns [48,68]. However, increasing the number of sensors beyond a certain point may not significantly enhance estimation quality, and trade-offs between accuracy, power usage, and cost must be considered [58,65].

The impact of changing body dynamics on data acquisition has been investigated, highlighting the influence of body position on signal reliability and the challenges of motion artifacts [49,67]. Nevertheless, certain setups have shown reliability, even during movement [61].

In conclusion, this SLR shed light on the methods, challenges, and potential future developments in using inertial sensors to assess adult human BP. The field holds promise, but addressing challenges related to sensor placement, motion artifacts, and algorithm development is crucial for its continued advancement. Future research should focus on expanding the application of these sensors to clinical settings and a broader range of populations, ultimately improving our understanding and management of respiratory health.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/a17060223/s1>, Table S1: Search strategy, string definition, and results; Table S2: Comparative assessment between the characteristics of the studies using inertial sensors for adult human BP assessment; Table S3: Reference device and applied data processing methods in the studies using inertial sensors for adult human BP assessment; Table S4: Acronyms/Abbreviations/Initialisms. Reference [70] is cited in Supplementary Materials.

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References

1. Boulding, R.; Stacey, R.; Niven, R.; Fowler, S.J. Dysfunctional Breathing: A Review of the Literature and Proposal for Classification. *Eur. Respir. Rev.* **2016**, *25*, 287–294. [CrossRef] [PubMed]
2. Bradley, D. Patterns of Breathing Dysfunction in Hyperventilation and Breathing Pattern Disorders. In *Recognizing and Treating Breathing Disorders—A Multidisciplinary Approach*; Chaitow, L., Bradley, D., Gilbert, C., Eds.; Elsevier Health Sciences: Edinburgh, UK, 2014; pp. 51–59, ISBN 978-0-7020-4980-4.
3. Malhotra, A.; Powell, F. Disorders of Ventilatory Control. In *Goldman-Cecil Medicine*; Goldman, L., Schafer, A.I., Eds.; Elsevier: Philadelphia, PA, USA, 2020; Volume 1, pp. 524–527.e2.
4. Vidotto, L.; de Carvalho, C.; Harvey, A.; Jones, M. Dysfunctional Breathing: What Do We Know? *J. Bras. Pneumol.* **2019**, *45*, e20170347. [CrossRef] [PubMed]
5. Chaitow, L.; Bradley, D.; Gilbert, C. The Structure and Function of Breathing. In *Recognizing and Treating Breathing Disorders—A Multidisciplinary Approach*; Chaitow, L., Bradley, D., Gilbert, C., Eds.; Elsevier Health Sciences: Edinburgh, UK, 2014; pp. 23–43, ISBN 978-0-7020-4980-4.

6. Lewit, K. Relation of Faulty Respiration to Posture, with Clinical Implications. *J. Am. Osteopath. Assoc.* **1980**, *79*, 525–529. [[PubMed](#)]
7. Bradley, H.; Esformes, J. Breathing Pattern Disorders and Functional Movement. *Int. J. Sports Phys. Ther.* **2014**, *9*, 28–39. [[PubMed](#)]
8. Chaitow, L. Breathing Pattern Disorders, Motor Control, and Low Back Pain. *J. Osteopath. Med.* **2004**, *7*, 33–40. [[CrossRef](#)]
9. Kolar, P.; Kobesova, A.; Valouchova, P.; Bitnar, P. Dynamic Neuromuscular Stabilization: Assessment Methods. In *Recognizing and Treating Breathing Disorders—A Multidisciplinary Approach*; Chaitow, L., Bradley, D., Gilbert, C., Eds.; Elsevier Health Sciences: Edinburgh, UK, 2014; pp. 93–98, ISBN 978-0-7020-4980-4.
10. Perri, M.A.; Halford, E. Pain and Faulty Breathing: A Pilot Study. *J. Bodyw. Mov. Ther.* **2004**, *8*, 297–306. [[CrossRef](#)]
11. Yach, B.; Linens, S.W. The Relationship Between Breathing Pattern Disorders and Scapular Dyskinesis. *Athl. Train. Sports Health Care* **2019**, *11*, 63–70. [[CrossRef](#)]
12. Takala, E.-P.; Pehkonen, I.; Forsman, M.; Hansson, G.-Å.; Mathiassen, S.E.; Neumann, W.P.; Sjøgaard, G.; Veiersted, K.B.; Westgaard, R.H.; Winkel, J. Systematic Evaluation of Observational Methods Assessing Biomechanical Exposures at Work. *Scand. J. Work Environ. Health* **2010**, *36*, 3–24. [[CrossRef](#)]
13. Gilbert, C. Psychological Training and Treatment of Breathing Problems. In *Recognizing and Treating Breathing Disorders—A Multidisciplinary Approach*; Chaitow, L., Bradley, D., Gilbert, C., Eds.; Elsevier Health Sciences: Edinburgh, UK, 2014; pp. 197–202, ISBN 978-0-7020-4980-4.
14. Baxter, K.; Courage, C.; Caine, K. Field Studies. In *Understanding your Users*; Baxter, K., Courage, C., Caine, K., Eds.; Interactive Technologies; Morgan Kaufmann: Boston, MA, USA, 2015; pp. 378–428, ISBN 978-0-12-800232-2.
15. Sakamoto, H.; Takamoto, H.; Matsui, T.; Kirimoto, T.; Sun, G. A Non-Contact Spirometer with Time-of-Flight Sensor for Assessment of Pulmonary Function. In Proceedings of the 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Montreal, QC, Canada, 20–24 July 2020; pp. 4114–4117.
16. Stubbe, L.; Houel, N.; Cottin, F. Accuracy and Reliability of the Optoelectronic Plethysmography and the Heart Rate Systems for Measuring Breathing Rates Compared with the Spirometer. *Sci. Rep.* **2022**, *12*, 19255. [[CrossRef](#)]
17. Romei, M.; Mauro, A.L.; D’Angelo, M.G.; Turconi, A.C.; Bresolin, N.; Pedotti, A.; Aliverti, A. Effects of Gender and Posture on Thoraco-Abdominal Kinematics during Quiet Breathing in Healthy Adults. *Respir. Physiol. Neurobiol.* **2010**, *172*, 184–191. [[CrossRef](#)]
18. Massaroni, C.; Carraro, E.; Vianello, A.; Miccinilli, S.; Morrone, M.; Levai, I.K.; Schena, E.; Saccomandi, P.; Sterzi, S.; Dickinson, J.W.; et al. Optoelectronic Plethysmography in Clinical Practice and Research: A Review. *Respiration* **2017**, *93*, 339–354. [[CrossRef](#)] [[PubMed](#)]
19. Aznar, M.C.; Persson, G.F.; Kofoed, I.M.; Nygaard, D.E.; Korreman, S.S. Irregular Breathing during 4DCT Scanning of Lung Cancer Patients: Is the Midventilation Approach Robust? *Phys. Med.* **2014**, *30*, 69–75. [[CrossRef](#)] [[PubMed](#)]
20. Enoz, M. Computed Tomography Scan of the Upper Airway Is Not Practical and Cost-Effective for Using Every Patient with Obstructive Sleep Apnea. *Otolaryngol. Head Neck Surg.* **2006**, *134*, 537. [[CrossRef](#)] [[PubMed](#)]
21. Kauczor, H.-U.; Hast, J.; Heussel, C.P.; Schlegel, J.; Mildemberger, P.; Thelen, M. CT Attenuation of Paired HRCT Scans Obtained at Full Inspiratory/Expiratory Position: Comparison with Pulmonary Function Tests. *Eur. Radiol.* **2002**, *12*, 2757–2763. [[CrossRef](#)] [[PubMed](#)]
22. Jakkaew, P.; Onoye, T. An Approach to Non-Contact Monitoring of Respiratory Rate and Breathing Pattern Based on Slow Motion Images. In Proceedings of the 2019 IEEE International Conference on Consumer Electronics—Asia (ICCE-Asia), Bangkok, Thailand, 12–14 June 2019; pp. 47–51.
23. Massaroni, C.; Lo Presti, D.; Formica, D.; Silvestri, S.; Schena, E. Non-Contact Monitoring of Breathing Pattern and Respiratory Rate via RGB Signal Measurement. *Sensors* **2019**, *19*, 2758. [[CrossRef](#)] [[PubMed](#)]
24. Romano, C.; Schena, E.; Silvestri, S.; Massaroni, C. Non-Contact Respiratory Monitoring Using an RGB Camera for Real-World Applications. *Sensors* **2021**, *21*, 5126. [[CrossRef](#)] [[PubMed](#)]
25. Wijenayake, U.; Park, S. Real-Time External Respiratory Motion Measuring Technique Using an RGB-D Camera and Principal Component Analysis. *Sensors* **2017**, *17*, 1840. [[CrossRef](#)]
26. Hsieh, C.-H.; Chiu, Y.-F.; Shen, Y.-H.; Chu, T.-S.; Huang, Y.-H. A UWB Radar Signal Processing Platform for Real-Time Human Respiratory Feature Extraction Based on Four-Segment Linear Waveform Model. *IEEE Trans. Biomed. Circuits Syst.* **2016**, *10*, 219–230. [[CrossRef](#)]
27. Wang, S.; Pohl, A.; Jaeschke, T.; Czaplik, M.; Köny, M.; Leonhardt, S.; Pohl, N. A Novel Ultra-Wideband 80 GHz FMCW Radar System for Contactless Monitoring of Vital Signs. In Proceedings of the 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Milan, Italy, 25–29 August 2015; pp. 4978–4981.
28. Lee, Y.; Pathirana, P.; Steinfort, C.; Caelli, T. Monitoring and Analysis of Respiratory Patterns Using Microwave Doppler Radar. *IEEE J. Transl. Eng. Health Med.* **2014**, *2*, 1–12. [[CrossRef](#)]
29. Miao, D.; Zhao, H.; Hong, H.; Zhu, X.; Li, C. Doppler Radar-Based Human Breathing Patterns Classification Using Support Vector Machine. In Proceedings of the 2017 IEEE Radar Conference (RadarConf), Seattle, WA, USA, 8–12 May 2017; pp. 0456–0459.
30. Ishrak, M.S.; Cai, F.; Islam, S.M.M.; Borić-Lubecke, O.; Wu, T.; Lubecke, V.M. Doppler Radar Remote Sensing of Respiratory Function. *Front. Physiol.* **2023**, *14*, 1130478. [[CrossRef](#)]
31. Purnomo, A.T.; Lin, D.-B.; Adiprabowo, T.; Hendria, W.F. Non-Contact Monitoring and Classification of Breathing Pattern for the Supervision of People Infected by COVID-19. *Sensors* **2021**, *21*, 3172. [[CrossRef](#)] [[PubMed](#)]

32. Abdelnasser, H.; Harras, K.A.; Youssef, M. UbiBreathe: A Ubiquitous Non-Invasive WiFi-Based Breathing Estimator. In Proceedings of the 16th ACM International Symposium on Mobile Ad Hoc Networking and Computing, Hangzhou, China, 22–25 June 2015; pp. 277–286.
33. Liu, X.; Cao, J.; Tang, S.; Wen, J.; Guo, P. Contactless Respiration Monitoring Via Off-the-Shelf WiFi Devices. *IEEE Trans. Mob. Comput.* **2016**, *15*, 2466–2479. [\[CrossRef\]](#)
34. Wang, X.; Yang, C.; Mao, S. PhaseBeat: Exploiting CSI Phase Data for Vital Sign Monitoring with Commodity WiFi Devices. In Proceedings of the 2017 IEEE 37th International Conference on Distributed Computing Systems (ICDCS), Atlanta, GA, USA, 5–8 June 2017; pp. 1230–1239.
35. Retory, Y.; Niedzialkowski, P.; De Picciotto, C.; Bonay, M.; Petitjean, M. New Respiratory Inductive Plethysmography (RIP) Method for Evaluating Ventilatory Adaptation during Mild Physical Activities. *PLoS ONE* **2016**, *11*, e0151983. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Bockenbauer, S.E.; Chen, H.; Julliard, K.N.; Weedon, J. Measuring Thoracic Excursion: Reliability of the Cloth Tape Measure Technique. *J. Am. Osteopath. Assoc.* **2007**, *107*, 191–196. [\[PubMed\]](#)
37. Malaguti, C.; Rondelli, R.R.; De Souza, L.M.; Domingues, M.; Dal Corso, S. Reliability of Chest Wall Mobility and Its Correlation with Pulmonary Function in Patients with Chronic Obstructive Pulmonary Disease. *Respir. Care* **2009**, *54*, 1703–1711. [\[PubMed\]](#)
38. Courtney, R.; Van Dixhoorn, J.; Cohen, M. Evaluation of Breathing Pattern: Comparison of a Manual Assessment of Respiratory Motion (MARM) and Respiratory Induction Plethysmography. *Appl. Psychophysiol. Biofeedback* **2008**, *33*, 91–100. [\[CrossRef\]](#) [\[PubMed\]](#)
39. Rajkumar, R.V. Breathing Rate/Rhythm Evaluation Ascertains Total Health (Breath): The Pulmonary Panacea. *Int. J. Physiother. Res.* **2020**, *8*, 3609–3619. [\[CrossRef\]](#)
40. Lim, S.; D'Souza, C. A Narrative Review on Contemporary and Emerging Uses of Inertial Sensing in Occupational Ergonomics. *Int. J. Ind. Ergon.* **2020**, *76*, 102937. [\[CrossRef\]](#) [\[PubMed\]](#)
41. Mengist, W.; Soromessa, T.; Legese, G. Method for Conducting Systematic Literature Review and Meta-Analysis for Environmental Science Research. *MethodsX* **2020**, *7*, 100777. [\[CrossRef\]](#)
42. Grant, M.J.; Booth, A. A Typology of Reviews: An Analysis of 14 Review Types and Associated Methodologies. *Health Inf. Libr. J.* **2009**, *26*, 91–108. [\[CrossRef\]](#)
43. Booth, A.; Sutton, A.; Papaioannou, D. *Systematic Approaches to a Successful Literature Review*, 2nd ed.; Sage: Los Angeles, CA, USA, 2016; ISBN 978-1-4739-1245-8.
44. Burnham, J.F. Scopus Database: A Review. *Biomed. Digit. Libr.* **2006**, *3*, 1. [\[CrossRef\]](#) [\[PubMed\]](#)
45. Birkle, C.; Pendlebury, D.A.; Schnell, J.; Adams, J. Web of Science as a Data Source for Research on Scientific and Scholarly Activity. *Quant. Sci. Stud.* **2020**, *1*, 363–376. [\[CrossRef\]](#)
46. PubMed Overview. Available online: <https://pubmed.ncbi.nlm.nih.gov/about/> (accessed on 23 May 2023).
47. White, J. PubMed 2.0. *Med. Ref. Serv. Q.* **2020**, *39*, 382–387. [\[CrossRef\]](#) [\[PubMed\]](#)
48. De la Fuente, C.; Weinstein, A.; Guzman-Venegas, R.; Arenas, J.; Cartes, J.; Soto, M.; Carpes, F. Use of Accelerometers for Automatic Regional Chest Movement Recognition during Tidal Breathing in Healthy Subjects. *J. Electromyogr. Kinesiol.* **2019**, *47*, 105–112. [\[CrossRef\]](#) [\[PubMed\]](#)
49. Dehkordi, P.K.; Marzencki, M.; Tavakolian, K.; Kaminska, M.; Kaminska, B. Validation of Respiratory Signal Derived from Suprasternal Notch Acceleration for Sleep Apnea Detection. In Proceedings of the 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Boston, MA, USA, 30 August–3 September 2011; pp. 3824–3827.
50. Fekr, A.R.; Radecka, K.; Zilic, Z. Design of an E-Health Respiration and Body Posture Monitoring System and Its Application for Rib Cage and Abdomen Synchrony Analysis. In Proceedings of the 2014 IEEE International Conference on Bioinformatics and Bioengineering, Boca Raton, FL, USA, 10–12 November 2014; pp. 141–148.
51. Fekr, A.R.; Radecka, K.; Zilic, Z. Tidal Volume Variability and Respiration Rate Estimation Using a Wearable Accelerometer Sensor. In Proceedings of the 2014 4th International Conference on Wireless Mobile Communication and Healthcare—Transforming Healthcare through Innovations in Mobile and Wireless Technologies (MOBIHEALTH), Athens, Greece, 3–5 November 2014; pp. 1–6.
52. Fekr, A.R.; Janidarmian, M.; Radecka, K.; Zilic, Z. Respiration Disorders Classification With Informative Features for M-Health Applications. *IEEE J. Biomed. Health Inform.* **2016**, *20*, 733–747. [\[CrossRef\]](#) [\[PubMed\]](#)
53. Gollee, H.; Chen, W. Real-Time Detection of Respiratory Activity Using an Inertial Measurement Unit. In Proceedings of the 2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Lyon, France, 22–26 August 2007; pp. 2230–2233.
54. Lapi, S.; Biagi, E.; Borgioli, G.; Calzolari, M.; Masotti, L.; Fontana, G. A Proposal of a Novel Cardiorespiratory Long-Term Monitoring Device. In Proceedings of the International Conference on Bio-Inspired Systems and Signal Processing BIOSTEC, Rome, Italy, 26–29 January 2011; pp. 38–42.
55. McClure, K.; Erdreich, B.; Bates, J.H.T.; McGinnis, R.S.; Masquelin, A.; Wshah, S. Classification and Detection of Breathing Patterns with Wearable Sensors and Deep Learning. *Sensors* **2020**, *20*, 6481. [\[CrossRef\]](#) [\[PubMed\]](#)
56. Rossi, M.; Sala, D.; Bovio, D.; Salito, C.; Alessandrelli, G.; Lombardi, C.; Mainardi, L.; Cerveri, P. SLEEP-SEE-THROUGH: Explainable Deep Learning for Sleep Event Detection and Quantification from Wearable Somnography. *IEEE J. Biomed. Health Inform.* **2023**, *27*, 3129–3140. [\[CrossRef\]](#)

57. Ryser, F.; Hanassab, S.; Lamercy, O.; Werth, E.; Gassert, R. Respiratory Analysis during Sleep Using a Chest-Worn Accelerometer: A Machine Learning Approach. *Biomed. Signal Process. Control* **2022**, *78*, 104014. [\[CrossRef\]](#)
58. Siqueira, A., Jr.; Spirandeli, A.F.; Moraes, R.; Zarzoso, V. Respiratory Waveform Estimation from Multiple Accelerometers: An Optimal Sensor Number and Placement Analysis. *IEEE J. Biomed. Health Inform.* **2019**, *23*, 1507–1515. [\[CrossRef\]](#)
59. Cesareo, A.; Gandolfi, S.; Pini, I.; Biffi, E.; Reni, G.; Aliverti, A. A Novel, Low Cost, Wearable Contact-Based Device for Breathing Frequency Monitoring. In Proceedings of the 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Jeju, Republic of Korea, 11–15 July 2017; pp. 2402–2405.
60. Frey, J.; Grabli, M.; Slyper, R.; Cauchard, J. ACM Breeze: Sharing Biofeedback Through Wearable Technologies. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, Montreal, QC, Canada, 21–26 April 2018.
61. Preejith, S.P.; Jeelani, A.; Maniyar, P.; Joseph, J.; Sivaprakasam, M. Accelerometer Based System for Continuous Respiratory Rate Monitoring. In Proceedings of the 2017 IEEE International Symposium on Medical Measurements and Applications (MeMeA), Rochester, MN, USA, 7–10 May 2017; pp. 171–176.
62. Yoon, J.-W.; Noh, Y.-S.; Kwon, Y.-S.; Kim, W.-K.; Yoon, H.-R. Improvement of Dynamic Respiration Monitoring Through Sensor Fusion of Accelerometer and Gyro-Sensor. *J. Electr. Eng. Technol.* **2014**, *9*, 334–343. [\[CrossRef\]](#)
63. Chang, H.; Wu, H.; Huang, P.; Ma, H.; Lo, Y.; Huang, Y. Portable Sleep Apnea Syndrome Screening and Event Detection Using Long Short-Term Memory Recurrent Neural Network. *Sensors* **2020**, *20*, 6067. [\[CrossRef\]](#) [\[PubMed\]](#)
64. Rubavathy, S.J.; Suresh, G.R.; Senthilkumar, C.; Bharathi, P.S.; Amudha, V. Wearable Sensor-Based Human Exhalation Rhythm Recognition Using Deep Learning Neural Network. In Proceedings of the 2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICES), Chennai, India, 15–16 July 2022.
65. Bates, A.; Ling, M.J.; Mann, J.; Arvind, D.K. Respiratory Rate and Flow Waveform Estimation from Tri-Axial Accelerometer Data. In Proceedings of the 2010 International Conference on Body Sensor Networks, Singapore, 7–9 June 2010; pp. 144–150.
66. Cesareo, A.; Previtali, Y.; Biffi, E.; Aliverti, A. Assessment of Breathing Parameters Using an Inertial Measurement Unit (IMU)-Based System. *Sensors* **2018**, *19*, 88. [\[CrossRef\]](#) [\[PubMed\]](#)
67. Das, P.S.; Ahmed, H.E.U.; Motaghedi, F.; Lester, N.J.; Khalil, A.; Janaideh, M.A.; Anees, S.; Carmichael, T.B.; Bain, A.R.; Rondeau-Gagne, S.; et al. A Wearable Multisensor Patch for Breathing Pattern Recognition. *IEEE Sens. J.* **2023**, *23*, 10924–10934. [\[CrossRef\]](#)
68. Gaidhani, A.; Moon, K.; Ozturk, Y.; Lee, S.; Youm, W. Extraction and Analysis of Respiratory Motion Using Wearable Inertial Sensor System during Trunk Motion. *Sensors* **2017**, *17*, 2932. [\[CrossRef\]](#)
69. Guul, M.; Jennum, P.; Sorensen, H. Portable Prescreening System for Sleep Apnea. In Proceedings of the 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Orlando, FL, USA, 16–20 August 2016; pp. 4917–4920.
70. Schäfer, A.; Kratky, K.W. Estimation of Breathing Rate from Respiratory Sinus Arrhythmia: Comparison of Various Methods. *Ann. Biomed. Eng.* **2008**, *36*, 476–485. [\[CrossRef\]](#)

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