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# Evolution of Bed-Based Sensor Technology in Unobtrusive Sleep Monitoring: A Review

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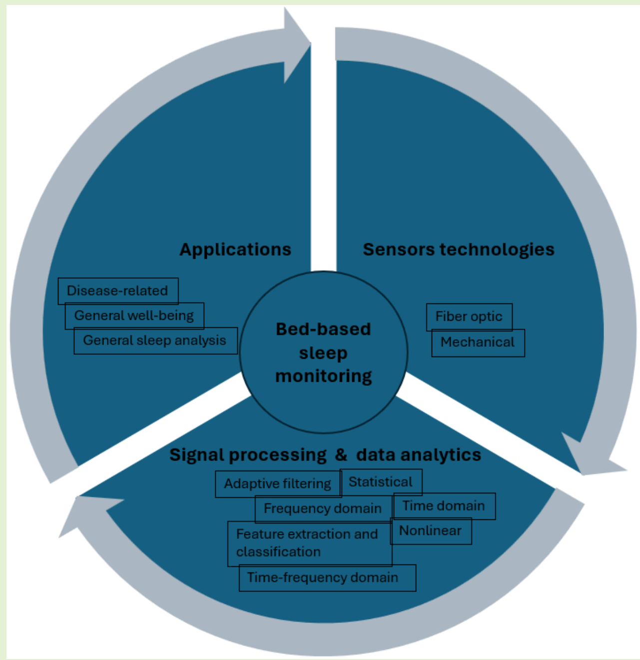
***Abstract*—With the emergence of new sensor technologies, such as fiber optic sensors (FOSs), compared to traditional mechanical sensors, unobtrusive sleep monitoring has been a research focus for decades. This work aims to provide a guide to current bed-based sensor technologies with diverse applications in various settings. We conducted a retrospective literature review, summarizing the state-of-the-art research over the past decade on non-contact bed-based sensor technology in sleep monitoring. We developed a three-category terminology: unobtrusive sensor technology, application, and subject. A total of 263 unique articles were acquired from three databases and screened for relevance, resulting in 21 papers selected for in-depth analysis. The findings revealed eight types of sensors: six mechanical sensors (pressure, accelerometer, piezoelectric, load cell, electromechanical film (EMFI), and hydraulic) and two FOSs (fiber Bragg grating and microbend FOS) that are integrated with or positioned under the bed at three levels of unobtrusiveness. We identified 15 parameters, with heart rate (14) and respiratory rate (13) being the most frequently measured. These parameters are generally categorized into three applications: disease-related diagnosis (18), general sleep analysis (9), and general well-being (11). The results indicated that sleep apnea (5) and insomnia (2) were the most frequently detected sleep disorders. Additionally, 59.1% (13) of the systems were tested in a lab environment, with only one undergoing clinical trials. In summary, there is a clear lack of convincing proof of the systems' effectiveness in continuous in-home sleep monitoring.**




***Index Terms*—Sleep, unobtrusive measurement, cardiorespiratory estimation, in-home continuous monitoring, fiber optic sensor.**

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## I. Introduction

### A. Unobtrusive Sleep Monitoring

SLEEP is more than just a period of inactivity; it is a dynamic state important for physical and mental health. Contrary to being passive, sleep engages the body in restorative processes, which affects daily function, performance, productivity, and long-term well-being. Physiologically, it influences functions such as tissue repair and protein synthesis - i.e., the key factors to physical recuperation. Neurologically, sleep facilitates memory consolidation, cognitive processing, and the removal of neurotoxic waste, ensuring optimal brain function, which affects learning, decision-making, and emotional regulation [1]–[3].

Sleep's importance extends to broader aspects of quantity, efficiency, well-being, disease management, and quality. As such, good quality of sleep is associated with improved mental health, evidenced by the link between sleep disruptions and disorders like depression and anxiety. Disturbances in sleep can precede various health conditions, including cardiovascular diseases, diabetes, and neurological disorders. Appropriate sleep can play its preventive role, enhancing the immune system, regulating hormonal balances, and sustaining metabolic functions [4], [5].

The importance of sleep, along with its quality and efficiency, is of major concern, especially regarding sleep-disordered diseases and their associated conditions. Sleep disorders affect millions globally and have far-reaching implications for various related diseases [6]. The American Sleep Association reports that 50-70 million US adults have a sleep disorder, with insomnia being the most common [7]. Sleep apnea affects approximately 25 million Americans. It is particularly of concern for its correlation with cardiovascular diseases such as hypertension, heart failure, and stroke [8]. Epidemiological data indicates that insomnia affects up to 30% of adults, and obstructive sleep apnea (OSA) impacts around 3-7% of men and 2-5% of women worldwide. Restless legs syndrome and narcolepsy, though less common, significantly impair quality of life (QoL). Chronic sleep deprivation, a common feature in many sleep disorders, correlates with increased risks of metabolic diseases, e.g. obesity, and negatively influences mental health conditions such as depression, anxiety, and even cognitive decline linked to neurodegenerative disorders like Alzheimer's and Parkinson's disease [9]. These statistics revealed the critical need to focus on sleep health and continuous monitoring as essential components in preventing and managing a wide array of health conditions, highlighting the significance of sleep in public health.

The sleep monitoring and evaluation field has experienced a paradigm shift from subjective, self-reported measures to objective, technology-driven assessments [10]. Historically, sleep analysis relied on subjective methods like sleep diaries and questionnaires, which were limited by personal bias and recall inaccuracies despite providing valuable insights into sleep patterns and disturbances. The advent of objective measurement technologies, such as polysomnography (PSG) and actigraphy, marked a significant advancement, offering more accurate and detailed analyses of sleep. PSG is considered the gold standard, i.e. reference for sleep evaluation, and it provides comprehensive data on sleep stages, respiratory events, and limb movements through various sensors and electrodes. Actigraphy employs wearable devices that track movement and infer sleep-wake cycles. It offers a less intrusive option for long-term monitoring compared to PSG. Integrating emerging technologies, including wearable biosensors and smart home systems, enhanced sleep assessment by continuously tracking physiological parameters like heart rate (HR), respiratory rate (RR), and body movements in real-time, even in a home setting. This transition towards objective, technology-based sleep evaluation improved diagnostic accuracy and enabled personalized treatment approaches, ultimately advancing sleep medicine and overall patient care [11], [12].

The evolution in sleep monitoring towards unobtrusive systems and the increasing emphasis on continuous, at-home monitoring reflected broader changes in healthcare priorities, emphasizing cost-effectiveness and preventive medicine. Traditional objective methods like PSG, while accurate, are often intrusive and primarily confined to clinical settings, posing limitations for long-term monitoring. This limitation has propelled the development and amplification of unobtrusive sleep monitoring technologies. These advancements align with the growing need for continuous health monitoring, allowing for the early detection and intervention of potential sleep disorders and related health conditions [13].

The advent of Ballistocardiography (BCG), an innovative method measuring mechanical cardiac activity through subtle body movements, facilitated this trend towards non-intrusive, home-based monitoring. BCG, integrated into everyday objects like beds and chairs, supports the continuous and passive monitoring of sleep patterns and cardiac health, offering a promising outcome for large-scale, longitudinal health studies and individualized healthcare strategies. This shift not only makes sleep monitoring more accessible and affordable but also aligns with the broader healthcare objective of transitioning from reactive to proactive and preventive care. By advancing such techniques and technologies, sleep medicine expands its diagnostic and therapeutic capabilities to play the role towards more patient-centric and preventative models [14], [15].

Integrating a wide range of sensor technology in BCG signal acquisition eased the unobtrusive, noninvasive, and continuous sleep monitoring, particularly in home settings. Traditional mechanical sensors, including force-sensitive resistors (FSR), accelerometers, hydraulic systems, piezoelectric elements, load cells, and more, integrated into mattresses detect and measure physical and physiological parameters such as body movement, HR, and RR, providing valuable data for sleep analysis [16]. For instance, accelerometers are widely used in tracking motion-related data, offering insights into sleep patterns and disturbances. Similarly, FSRs embedded in mattresses detect pressure changes caused by body movements, aiding sleep stage identification. Piezoelectric sensors, recognized for their sensitivity, capture physiological movements, including heartbeat and breathing patterns. While these traditional sensors have facilitated significant advancements in sleep monitoring, they have certain limitations, such as susceptibility to motion artifacts, accuracy, and limited data types [17].

Using the principles of light transmission and modulation within optical fibers, these sensors can detect a broader range of physiological signals with greater precision. This includes subtle body movements and heart rate variability (HRV). The advantages of such technologies lie in their enhanced accuracy, improved signal processing, and expanded parameter extraction, leading to a more comprehensive understanding of sleep quality and disturbances. Despite offering several advantages, the fiber optic sensors (FOSs) suffer from the expense, complex installation, fragility, integration, and data processing sophistication due to the high volume of data [18].

A low signal-to-noise ratio, external movements, and motion artifacts are often the technical difficulties that make it challenging to extract accurate sleep-related data. Its sensitivity and dependability to sleeping positions and the type of bed or mattress can lead to inconsistent readings. Moreover, isolating and interpreting the BCG signal for physiological and environmental noise demands complex signal processing techniques, consuming considerable computation resources. In addition to pre-processing of the signal, advanced filtering and signal processing methods such as wavelet transformation, Fourier analysis, or adaptive filtering can often be employed to separate an actual cardiac/respiration signal from noise. These algorithms enhance the signal quality, making it more representative of the actual physiological signal and providing critical insights into sleep quality. Furthermore, machine learning algorithms can be used to classify and interpret BCG data, leading to the extraction of various sleep-related parameters such as HR, RR, and even sleep stages [19], [20].

Thus, the chain of sensor technology (affecting signal quality), supported with signal processing (affecting parameter extraction), and post-processing combined with the data analysis (affecting application and sleep-related diseases and associated diagnosis) influence the results and consequently the sensor deployment and level of unobtrusiveness, as well as applications and user experiences.

The emergence of newer technologies, like FOS and their variants, such as fiber Bragg Grating (FBG) and micro bend fiber optic sensors (MFOS), addresses these limitations and extends the capabilities of sleep monitoring systems. The FOS, known for their high sensitivity and accuracy, are increasingly being adopted for sleep studies.

### *B. Fundamental Operation of Mechanical Sensors*

FSRs are devices that change their electrical resistance in response to an applied force [21]. These sensors consist of a conductive polymer that varies its resistance with the force applied to its surface. The fundamental operation involves placing the FSR between two conductive layers, where the force exerted on the sensor compresses the conductive particles within the polymer, decreasing the resistance. Mathematically, the relationship between force and resistance is often non-linear, but it can be approximated by the formula: $R = \frac{1}{F^n}$, where: $R$ is the resistance, $F$ is the applied force, and $n$ is a material-dependent constant.

Piezoelectric sensors operate based on the piezoelectric effect, where certain materials generate an electric charge in response to applied mechanical stress [22]. These sensors typically use piezoelectric crystals or ceramics that produce a voltage proportional to the force or pressure exerted on them. When a mechanical force is applied to the piezoelectric material, it deforms and creates an electric field, resulting in a measurable voltage output. This property makes piezoelectric sensors ideal for applications requiring dynamic pressure, force, or vibration measurements. Mathematically, the generated charge $Q$ in a piezoelectric material is proportional to the applied force $F$ and can be expressed as: $Q = d \cdot F$, where: $Q$ is the generated charge, $d$ is the piezoelectric charge coefficient (material-dependent), and $F$ is the applied force. The resulting voltage $V$ across the piezoelectric material can be related to the charge by: $V = \frac{Q}{C}$, where: $V$ is the voltage, $Q$ is the generated charge, and $C$ is the capacitance of the piezoelectric material.

Accelerometers are sensors designed to measure the acceleration [23]. They typically consist of a microelectromechanical system (MEMS) structure that includes a mass attached to a spring within a housing. When the sensor experiences acceleration, the mass deflects, causing a change in capacitance, resistance, or other electrical properties that can be measured. This deflection is proportional to the applied acceleration, allowing the sensor to determine the acceleration along one or more axes. The fundamental equation for an accelerometer's operation is based on Newton's second law of motion: $F = m \cdot a$, where: $F$ is the force exerted on the mass, $m$ is the mass, and $a$ is the acceleration. The resulting displacement $x$ of the mass due to the force can be described by Hooke's law: $F = k \cdot x$, where: $F$ is the force, $k$ is the spring constant, and $x$ is the displacement of the mass. By combining these equations, the acceleration can be related to the displacement: $a = \frac{k}{m} \cdot x$. In MEMS accelerometers, the displacement $x$ often causes a change in capacitance, which can be measured and related to the acceleration. This change in capacitance $C$ can be expressed as: C = $\frac{\epsilon A}{d-x}$, where: $C$ is the capacitance, $\epsilon$ is the permittivity of the dielectric material, $A$ is the area of the capacitor plates, and $d$ is the initial separation between the plates.

Strain gauge sensors operate by measuring the amount of deformation or strain in an object [24]. These sensors consist of a conductive material pattern that deforms along with the object to which it is attached. When the object experiences strain, the deformation causes a change in the electrical resistance of the strain gauge. This change in resistance can be measured and related to the amount of strain experienced by the object. Strain gauges are commonly used in structural health monitoring, material testing, and mechanical engineering applications. The relationship between the strain $\epsilon$ and the change in resistance $\Delta R$ of the strain gauge is given by the gauge factor $GF$, which is defined as: $GF = \frac{\Delta R/R}{\epsilon}$, where: $GF$ is the gauge factor, $\Delta R$ is the change in resistance, $R$ is the original resistance, and $\epsilon$ is the strain. The strain $\epsilon$ itself is defined as the change in length $\Delta L$ divided by the original length $L$: $\epsilon = \frac{\Delta L}{L}$ By measuring the change in resistance $\Delta R$ and knowing the gauge factor $GF$, the strain can be calculated as: $\epsilon = \frac{\Delta R}{R \cdot GF}$

Load cells are transducers that convert mechanical force into an electrical signal [25]. They typically consist of a metal body (the load cell) with strain gauges bonded to it. When a force is applied to the load cell, it deforms slightly, causing the strain gauges to change their resistance. This change in resistance is proportional to the applied force and can be measured using a Wheatstone bridge circuit. The output voltage from the Wheatstone bridge is then calibrated to determine the applied force. Load cells are widely used in weighing systems, industrial scales, and force measurement applications. The relationship between the applied force $F$ and the strain $\epsilon$ experienced by the load cell can be described by Hooke's law: $\epsilon = \frac{F}{EA}$, where: $\epsilon$ is the strain, $F$ is the applied force, $E$ is the Young's modulus of the load cell material, and $A$ is the cross-sectional area of the load cell. The strain $\epsilon$ causes a change in resistance $\Delta R$ of the strain gauges, which is related to the original resistance $R$ and the gauge factor $GF$: $\Delta R = R \cdot GF \cdot \epsilon$

The Wheatstone bridge circuit is used to measure this change in resistance, and the output voltage $V_{out}$ of the Wheatstone bridge is given by: $V_{out} = V_{in} \cdot \frac{\Delta R}{R+\Delta R}$ where: $V_{out}$ is the output voltage, $V_{in}$ is the input excitation voltage, and $\Delta R$ is the change in resistance. By calibrating the output voltage $V_{out}$ with known forces, the applied force $F$ can be determined accurately.

### C. Fundamental Operation of FOSs

Fiber optic sensors operate by transmitting light through optical fibers and measuring changes in the light's properties as it interacts with environmental factors such as temperature, pressure, or strain. The fundamental principle involves a light source, typically a laser, that injects light into the fiber, where it travels through the core. Any external perturbations cause alterations in the light's intensity, phase, polarization, or wavelength, which are detected at the other end by a photodetector. Mathematically, the light intensity $I$ along the fiber can be described by I = I$_0 e^{-\alpha L}$ $: where I$ is the light intensity at a given point along the fiber, $I_0$ is the initial light intensity, $\alpha$ is the attenuation coefficient, and $L$ is the length of the fiber. Changes in environmental conditions modify the attenuation coefficient $\alpha$, leading to variations in the detected light intensity, which can be quantified and analyzed to determine the corresponding physical changes.

Fiber Bragg Gratings (FBGs) are a type of fiber optic sensor that consists of periodic variations in the refractive index along a segment of the optical fiber [26]. These variations create a wavelength-specific reflector. When broadband light passes through the fiber, specific wavelengths, known as Bragg wavelengths, are reflected back while other wavelengths pass through. This reflection occurs due to the periodic grating structure inscribed in the fiber core, and the Bragg wavelength shifts in response to changes in temperature or strain. The Bragg wavelength $\lambda_B$ is determined by the grating period $\Lambda$ and the effective refractive index $n_{eff}$ of the fiber, and it can be expressed as $\lambda_B = 2n_{eff}\Lambda$. The shift in Bragg wavelength $\Delta\lambda_B$ due to strain $\Delta\epsilon$ and temperature $\Delta T$ can be described by: $\Delta\lambda_B = \lambda_B(k_e\Delta\epsilon + k_T\Delta T), where : \Delta\lambda_B$ is the change in Bragg wavelength, $\lambda_B$ is the initial Bragg wavelength, $k_e$ is the strain sensitivity coefficient, $\Delta\epsilon$ is the change in strain, $k_T$ is the temperature sensitivity coefficient, and $\Delta T$ is the change in temperature. FBGs are highly sensitive to changes in strain and temperature, making them effective for precise monitoring applications.

Micro-bending fiber optic sensors detect changes in light transmission due to small, localized bends in the optical fiber [27]. These bends can be caused by external forces such as pressure, deformation, or strain. The micro-bends induce local variations in the fiber's curvature, causing light to scatter out of the core and leading to increased attenuation of the light signal. The degree of attenuation correlates with the extent of bending, making it possible to measure the applied force or pressure. Mathematically, the light loss due to micro-bending can be expressed by the power loss $P$, which depends on the bend radius $R$ and the spatial frequency of the bends. The power attenuation coefficient $\alpha_b$ due to micro-bending is given by: $\alpha_b = \frac{\gamma}{R^2}$, where: $\alpha_b$ is the attenuation coefficient, $R$ is the bend radius, and $\gamma$ is a constant dependent on the fiber's properties. The total power loss $P$ can be expressed as: $P = P_0 e^{-\alpha_b L}$, where: $P$ is the transmitted power after attenuation, $P_0$ is the initial power, $\alpha_b$ is the attenuation coefficient, and $L$ is the length of the fiber affected by bending. These relationships allow the quantification of light loss due to micro-bending, enabling the measurement of physical forces applied to the fiber.

### D. Our Contributions

This work is an effort to review, monitor, extract, and analyze the trend of technological advancements in the sensor and its application during the last ten years in sleep medicine. We tried to consider and chain the various factors and aspects of the technologies affecting the level of readiness and articulate the barriers from sleep lab measurement and validation to clinical trials, home settings, and continuous use. This work further contributes to how the technology shift from the traditional mechanical sensors to more advanced FOSs could have influenced the system's application and its usability in terms of user experiences and clinical acceptance. We also give an insight into the potential and capability of unobtrusive, noninvasive, and nonintrusive sleep monitoring systems in sleep-related and non-sleep-related disease management and diagnostics. In addition, we also discuss the perspective and possible future direction.

The rest of this paper is as follows: Section II presents the method and terms used to perform the literature review and extract the information. In Section III, we present the results and address the key points articulated in the earlier section. Sections IV and V discuss and interpret the results and conclude the work with the take-home messages.

## II. Material and Methods

The terms "unobtrusive," "noninvasive," and "nonintrusive" in the context of sleep monitoring encompass the utilization of technology to collect data on an individual's sleep-related parameters, patterns, and quality without causing disruptions to their sleep, necessitating bodily insertion of devices, or violating their privacy. These terminologies have played key roles in enhancing user experiences, promoting technology acceptance, and facilitating the transition from in-laboratory system validation to practical implementation in home environments and beyond for continuous monitoring of sleep-related metrics [17].

Primarily, the unobtrusiveness of a sleep monitoring system is contingent upon the underlying sensor technology - i.e., its operational principles and, subsequently, how these sensors are deployed. Furthermore, the accuracy of the measurements is influenced by signal processing techniques on one hand and the quality of the acquired data from the sensors on the other. Establishing a connection between sensor technology and signal processing enables the extraction of crucial sleep-related parameters that define the utility of the monitoring system.

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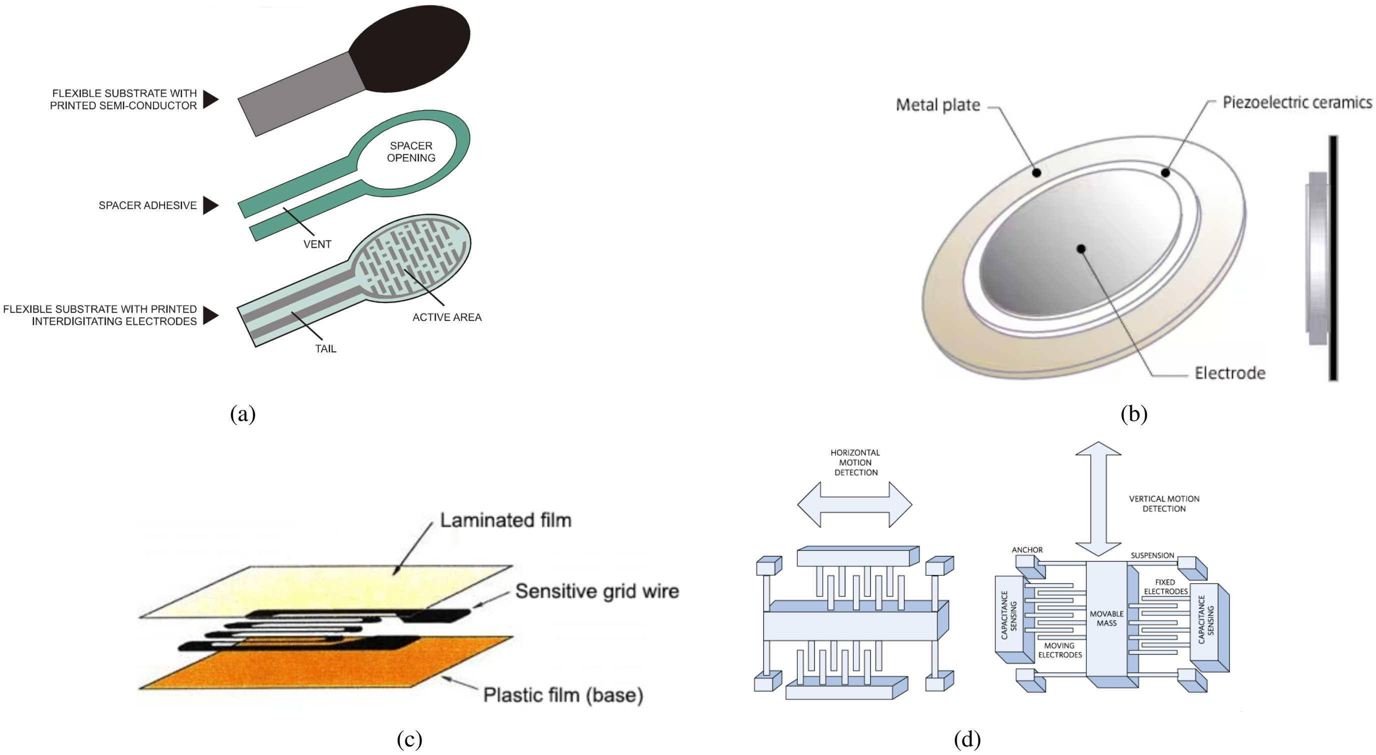


Fig. 1: Fundamental principles and structures of four main mechanical sensors in unobtrusive sleep monitoring. (a) FSR: changes its resistance based on the force applied. (b) Piezoelectric: generates an electrical charge in response to mechanical stress. (c) Strain Gauge: changes resistance when deformed. (d) Accelerometer: measures acceleration by detecting the deflection of a mass within a MEMS structure.

Consequently, the choice of sensors, signal processing techniques, specific parameters extracted, and overall data processing strategies becomes paramount, directly influencing the monitoring system's intended application. This application can vary, encompassing tasks such as disease diagnosis, monitoring general well-being, and early detection of sleep-related issues. These considerations are also intrinsically tied to the technological readiness level in the system environment and the practical deployment scenario.

Depending on the application, intention, and level of readiness, the sleep monitoring system could be utilized in clinical trials, home environments, in-lab validation, and sleep lab environments or beyond.

## A. Sensor Technology

Sensor technology is crucial in advancing in-home, remote, and unobtrusive sleep monitoring. It is the fundamental enabler for achieving objectives related to system accuracy, unobtrusiveness, and user experience enhancement.

*1) Mechanical sensors:* : Traditional mechanical sensors encompass a diverse array of sensor technologies, including piezoelectric sensors, accelerometers, force/pressure sensors, inertial measurement units (IMU), hydraulic systems, strain gauges, load cells, and more. These sensors operate based on physical principles to measure and monitor various sleep-related parameters. They are known for their cost-effectiveness, efficiency, ability to provide a certain level of accuracy, and adaptability for deployment across various levels of unobtrusiveness in sleep monitoring applications.

*2) Fiber optic sensors:* : Demanding higher precision, elevated signal quality, enhanced comfort, suitability for clinical applications, and the integration of technological advancements have propelled the utilization of FOSs in sleep monitoring. In contrast to conventional mechanical sensors, FOSs present advantages that include heightened accuracy, an elevated level of unobtrusiveness, and the disadvantage of expense. These attributes position the FOSs as well-suited for sleep-related disease diagnosis and comprehensive sleep assessment applications.

## B. System Deployment and Level of Unobtrusiveness

We considered three levels of unobtrusiveness that align with an individual's comfort preferences and privacy concerns. Unobtrusive-L1 provides the highest level of separation from sensors, while Unobtrusive-L3 offers a compromise between unobtrusiveness and sensor proximity. The system choice can depend on the user's comfort, data accuracy requirements, and personal preferences.

*1) Unobtrusive-L1 (level 1):* In Unobtrusive-L1, the sensors and the monitoring system are deployed under the mattress. This ensures that the user has no direct contact with the sensors. Examples of Unobtrusive-L1 systems include BCG systems that measure body movement, respiration, and HR without any visible sensors or attachments.

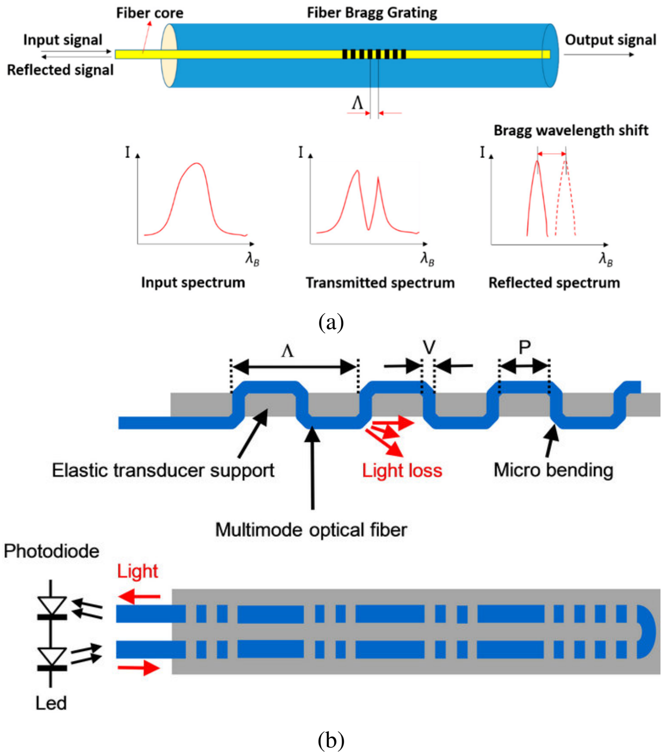


Fig. 2: Fundamental operation of optical sensors. (a) Fiber Bragg Grating: reflects specific wavelengths of light, which shift in response to strain or temperature changes in the fiber. (b) Microbending: detects variations in light transmission caused by microbends in the optical fiber, which occur due to external forces or pressure.

*2) Unobtrusive-L2 (level 2):* In Unobtrusive-L2, the sensors are deployed in the mattress or a pillow, closer to the user than Unobtrusive-L1. While still relatively unobtrusive, the user may have some contact with the sensors, such as lying on a mattress with integrated sensors or resting their head on a pillow with embedded technology. Examples of Unobtrusive-L2 systems include smart mattresses or pillows with built-in sensors for sleep tracking.

*3) Unobtrusive-L3 (level 3):* In Unobtrusive-L3, the sensors are deployed on the mattress but still do not have direct contact with the user. This involves placing sensors on the mattress surface, typically beneath a fitted sheet or mattress cover, ensuring that the user does not come into direct contact with the sensors. Examples of Unobtrusive-L3 systems include bed-based sensor arrays that detect movements, HR, and respiration through the mattress without direct contact.

## C. Technology Readiness

In general, we have considered four levels of readiness, addressing:

*1) In-lab validation:* These systems may undergo in-lab validation studies to assess their accuracy and reliability in controlled environments. This step is crucial before applying them in clinical or research settings and home environments. The pre-requisite is to ensure the monitoring system can produce consistent and reliable results compared to established sleep monitoring methods. This step requires frequent tests of the system's basic functionality (e.g., calibration, recalibration, frequency adjustment, data acquisition, and processing).

*2) Home environment:* Such systems are typically used for personal sleep tracking, disease diagnosis, and to identify potential sleep disorders. They provide insights into sleep routines, habits, and overall sleep health. Compared to the clinical trial system, they may have lower accuracy and acceptance but are suitable for self-monitoring and general sleep assessment.

*3) Sleep Lab:* Sleep labs equipped with PSG systems are considered the gold standard for comprehensive sleep monitoring. They are used for diagnosing sleep disorders, such as sleep apnea, insomnia, and narcolepsy. A high level of readiness is essential for using sleep monitoring systems in sleep labs.

*4) Clinical Trial:* A sleep monitoring system is often used in clinical trials to assess the impact of interventions, treatments, or medications on sleep quality, sleep-related cardiorespiratory measurement, and patterns. In some cases, it can also contribute to monitoring adverse or side effects. Usually, only a system with a high level of readiness could be used in clinical trials, as it requires consistency in operation, data accuracy, and reliability for evaluating treatment efficacy and safety.

## D. Signal Processing and Data Analysis

Signal processing and data analysis techniques significantly influence the application of a sleep monitoring system by determining the parameters extracted. Classifying different sleep stages based on physiological signals and movement provides insights into sleep quality and patterns. Sleep efficiency (SE) is another key metric, reflecting the effectiveness of sleep and identifying potential disturbances. This relies on robust sensor technology, signal processing, and data analysis. Effective long-term data analysis can identify patterns in sleep cycles, track trends, and translate complex data into user-friendly insights. This approach aids in early detection of sleep-related disorders and health conditions, enabling timely interventions and improved outcomes.

We have categorized the signal processing and data analysis techniques:

*1) Time-Domain analysis:* Is based on amplitude, width, and characteristic changes over time that result in detecting and measuring time-based events such as peak detection in BCG signals.

*2) Frequency-Domain analysis:* Is based on the frequency content to understand the signal components in terms of frequency, like identifying dominant frequencies.

*3) Time-Frequency analysis:* Is the simultaneous analysis of both time and frequency characteristics to analyze the signals with time-varying frequency content, which cannot be adequately described by just time or frequency domain methods alone.

*4) Nonlinear analysis:* Is analyzing the nonlinear dynamics of signals to uncover complex behaviors in signals that are not evident with linear methods, such as chaos or fractal analysis in HRV.

*5) Statistical analysis:* Is applying statistical methods to understand and interpret signal data for statistical characterization, hypothesis testing, and building predictive models based on signal data.

*6) Feature extraction and classification:* Is identifying distinctive features in a signal and categorizing them to extract relevant features for tasks like disease diagnosis or sleep stage classification, often using machine learning algorithms.

*7) Adaptive filtering:* Is filtering that adapts to changing signal characteristics to remove unwanted components from a signal, such as noise, in real-time processing, where signal properties can vary.

## E. Extracted Parameters

Various aspects of health, including physical and mental well-being, sleep quality, and health conditions, are interconnected. These can be assessed through a combination of sleep-related and physiological measurements. This approach provides a comprehensive understanding of an individual's overall health and sleep-related issues. Some of the most important and frequent parameters that can be objectively measured are as:

*1) Physiological parameters:* Parameters such as HR, RR, inter-beat interval (IBI), and HRV can contribute to identifying the risk factors for cardiovascular diseases, such as hypertension and heart diseases, spikes or irregularities, stress, anxiety, autonomic nervous system activity, assessing the overall health, the respiratory system, sleep quality, and early detection of respiratory conditions or disorders such as asthma, chronic obstructive pulmonary disease (COPD), or sleep-related breathing disorders like sleep apnea, lung function, and sleep-related breathing disturbances, insomnia symptoms, restless leg syndrome, involuntary limb movements during sleep.

*2) Non-physiological sleep-related parameters:* Body movements, including motion analysis, sleeping positions, and posture, are the other categories of metrics that are often measured and monitored during sleep and are used to track physical activity levels, restlessness, overall mobility, and comfort.

Sleep staging (both physiological and non-physiological may contribute), efficiency, and quality are among the other most important metrics contributing to sleep architecture. In addition, overall sleep quality, sleep depth, circadian rhythms, sleep duration, total sleep time (TST), time spent awake in bed, the effectiveness of sleep, sleep continuity, insomnia symptoms, overall comfort, perceived sleep satisfaction, and disruptions are the metrics and parameters that often are measured.

Environmental factors such as noise, light intensity, and temperature are the other parameters that can influence sleep quality and efficiency, particularly for those suffering from/diagnosed with sleep-related/chronic diseases.

## F. System Application

The application could be diverse , from general health and well-being to sleep-related/non-sleep-related disease diagnosis.

*1) General health and well-being:* The subject's overall health status can be tracked and assessed via sleep quality and vital signs such as cardiorespiratory and blood pressure. Moreover, insights into daily routines and habits can help optimize one's lifestyle. This can assist in adjusting the lifestyle to improve the overall well-being. In addition, continuous monitoring of key health indicators and frequent enhancement via practices can improve daily physical and mental performance.

*2) General sleep analysis:* Many sleep monitoring systems are designed to evaluate sleep quality by tracking parameters such as sleep duration, SE, and sleep stages. Insights gained from routine and sleep analysis can guide adjustments to improve sleep habits, thereby enhancing overall well-being, health, daily performance, and cognitive function.

*3) Disease-Related:* Monitoring vital signs such as HR, RR, oxygen saturation, and other relevant metrics during sleep can help to assess and manage cardiovascular and respiratory conditions. It also aid in the early detection of sleep disorders such as sleep apnea, insomnia, restless leg syndrome, and narcolepsy. Managing chronic diseases, including cardiovascular disease, asthma, COPD, and respiratory conditions, is another application of sleep monitoring systems. It involves understanding how health metrics and sleep patterns impact individual conditions.

## G. Literature Retrieval

The search string we developed reflects two major aspects as the core, such as:

*1) Search strategy:* Unobtrusive and noninvasive technologies, subjects and applications, hence:

Unobtrusive and noninvasive technologies: focused on the sensor technologies deployed on/in/beneath and in bed without direct contact with the subjects. This included both traditional sensor technologies as well as fiber optic technologies. To capture this dimension, our terminology included "mechanical sensors," "force-sensitive resistors," "pressure sensors," "load cells," "fiber optic," "optical fiber sensors," "fiber Bragg grating," "micro bend," among others. We also considered various synonyms and terminological variations.

Subject and application: Our search terms spanned various participant categories and monitoring settings. This included terms that pertain to the participants involved in the experiments (e.g., "patients," "healthy subjects," "sleep-disordered," "hospital discharged") and the contexts of application (e.g., "well-being," "general health monitoring," "general sleep monitoring," "early abnormalities detection," "sleep-related disease diagnosis," "progress assessment"). We also included specific terms like "clinical trials" and "sleep measurements.".

The search strings were constructed using the operators "OR" and "AND" to combine these terms. This approach was applied consistently across three major databases: IEEE Xplore, PubMed, and Scopus, encompassing a period of nearly a decade from January 2014 to May 2023. We limited our search to English-language publications released within this time frame. Subsequently, we amalgamated all retrieved records into a single dataset, removed duplicates, and screened titles and abstracts, primarily to eliminate irrelevant studies in the initial phase. We analyzed the remaining studies in the subsequent phase, extracting and emphasizing the pre-defined information.

*2) Review Criteria:* Inclusion and exclusion, thus:

Three persons performed a two-stage review. We defined clear inclusion/exclusion review criteria to maintain the consistency of the extracted information.

Inclusion Criteria:

- Studies employing non-contact sensor technologies that do not interfere with the subject's sleep were included.
- Data collection was limited to instances when the individual was in bed.
- Only studies involving human subjects were considered.
- The sleep monitoring system must have undergone at least a validation process.

Exclusion Criteria:

- Studies involving wearable devices were excluded.
- Research focusing on animal subjects was not included.
- Studies that solely relied on previously collected databases were omitted.
- Reviews, surveys, conference papers, and non-English language research were not considered.
- Data obtained from subjects seated on chairs or not in a bed were excluded.
- Studies incorporating camera or radar technologies for monitoring were omitted.

*3) Patent Search:* Additionally, a preliminary search was conducted to identify patents meeting the specified search criteria. The databases utilized included WIPO, USPTO, Google Patents, DPMAregister, and DEPATISnet. Keywords were searched within the titles, abstracts, and claims of the patents. Patents incorporating acoustic sensors, radar-based sensors, implantable sensors, wearable sensors, or other systems with sensors that directly contact the body were excluded from this review. Only patents available in English and not withdrawn at the time of the search were considered. However, due to the lack of significant information and the different nature of the work, we have chosen to present the results separately to maintain consistency.

## III. Results

### A. Sensor Technology

We identified 21 works, of which 17 utilized various mechanical sensors and four employed FOSs (Table I and II). Mechanical sensors demonstrated consistent application over a decade, with a significant increase in 2017. Conversely, the deployment of FOSs was primarily recorded in 2017 (see Fig. 3).

We identified six distinct technologies for mechanical sensors, with piezoelectric sensors (6) and pressure sensors (5) contributing the largest proportions. Other technologies included accelerometers (4), electromechanical film (EMFI) sensors (2), load cells (1), and hydraulic systems (1). Of the 17 mechanical sensor implementations, four integrated sensor fusion strategies, incorporating a blend of pressure sensors and accelerometers (3) and EMFI with load cells (1) - (see Fig. 4 - bottom).

Regarding fiber optic technology, MFOS showed a clear dominance, possibly due to their integration and adaptability to various measurements. FBG sensors, while less prevalent, underscore their importance in the overall sensor technology landscape for sleep monitoring (see Fig. 4 - top).

### B. Level of Unobtrusiveness

We categorized the data into three levels of unobtrusiveness for sleep monitoring systems.

Unobtrusive-L1: This category occupied the largest portion at 57.1% (12). This indicated that most evaluated technologies were considered Unobtrusive-L1, which are the least invasive or most seamlessly integrated into the user's environment or routine.

Unobtrusive-L2: The second-largest category, with 33.3% (7), represented a moderate level of unobtrusiveness offering a balance between functionality and user comfort, maintaining a certain degree of accuracy and reliability.

Unobtrusive-L3: The smallest segment, at 9.5% (2), represented the least unobtrusive level. This might be due to their need for user interaction and the complexity of the technology (see Fig. 5).

### C. Extracted Parameters

We observed that the most frequently measured parameters are HR (14) and RR (13), which signifies the predominant role in sleep studies.

Sleep stages, often refer to the classification of sleep into wake, N1, N2, N3, and rapid eye movement (REM), of which N1 to N3 are considered non-rapid eye movement (NREM), also showed a high frequency of measurement (5), indicating a significant focus on sleep quality and architecture in research. Body movement metrics have a slightly lower frequency (3) but are nonetheless a key aspect of sleep monitoring, used to assess restlessness or sleep disturbances, and one of the fusion metrics in sleep stage identification.

TST and SE are measured with moderate frequency (2), reflecting their relevance in assessing the quantity and quality of sleep and contributing to sleep efficiency and some sleep-related diseases such as insomnia.

The parameters HRV and IBI are measured less frequently (2) than other physiological metrics but still hold considerable significance in sleep studies relating to the analysis of autonomic nervous system activity during sleep, stress, sleep quality, and general health and well-being.

Sleep onset delay (SOD), respiration rhythm, sleeping position, body posture, torso localization, and movement rate are among the parameters with lower frequencies of measurement (1). These may represent more specific aspects of sleep behavior and physiology. The latter four correlate with body movement and can stand in a similar category.

Finally, rapid/shallow respiration duration stands with a frequently measured parameter of one.

Overall, our analysis reflects the multidimensional nature of sleep monitoring, where a range of parameters is essential

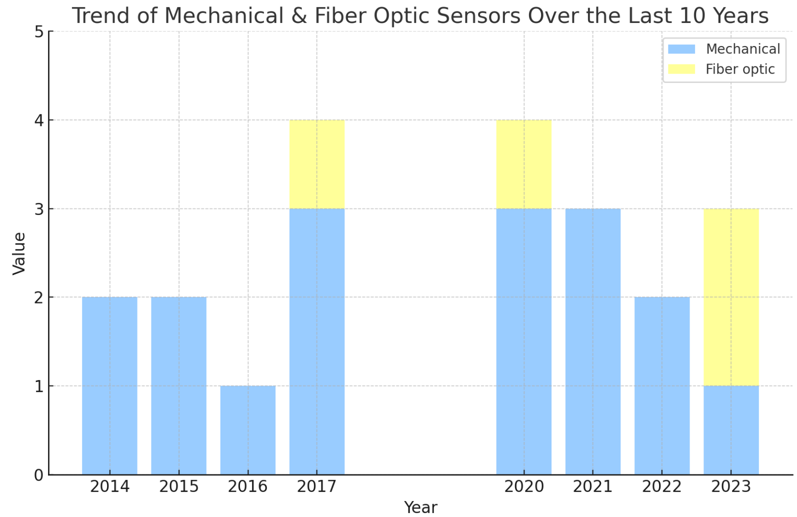


Fig. 3: The application of FOSs in sleep monitoring systems regains interest in 2020, while the mechanical sensors prove their applicability with the consistent presence. The year 2023 might be the first trigger point in the trend shift from the traditional mechanical sensors to the newer emerging technologies. However, care must be taken that this work only covers the publication until May 2023.

for a comprehensive understanding of sleep quality and health implications aimed at different applications, target groups, and environments (see Fig. 6 and 7).

## *D. Signal Processing and Data Analysis*

In total, 39 signal processing techniques and data analysis have been applied, of which moving average, adaptive window, and bi-directional long short-term memory (Bi-LSTM) has appeared two times and the remaining one time. Care must be taken that the difference is minor in some techniques, but we have remained faithful to the original paper.

The time-domain category builds the largest position with 13, including techniques such as adaptive threshold, simple derivative, and 200-order finite impulse response (FIR) filtering. Frequency-domain techniques include six techniques, including feature discrete Fourier transform (DFT) and fast Fourier transform (FFT) spectrum analysis. Adaptive filtering with six techniques, such as the Hanning window and various band pass filters (BPFs), highlights its importance. The Statistical segment, including six techniques, highlights methods like Naïve Bayes and Random Forest, which suggest a focus on machine learning approaches within signal processing. Feature extraction and classification encompass five techniques, including adaptive threshold and Bi-LSTM (2), pointing to advanced analytics and data-driven modeling. The nonlinear section is smaller, indicating fewer techniques, with Bayesian fusion being a notable method. Lastly, Time-frequency analysis with four techniques includes sliding window Fourier transform, and wavelet transforms, which are crucial for analyzing non-stationary signals (see Fig. 8).

## *E. Application*

Disease-related application is the largest segment, indicating the primary use of sleep monitoring systems in disease management and diagnosis. It includes cardiovascular (6), apnea (5), insomnia (2), nocturnal HR (1), heart failure (1), stroke (1), snoring (1), and respiration rhythm (1).

General well-being represented a slightly smaller segment. This category emphasizes the use of sleep monitoring for overall health and wellness, which includes respiration (7) and cardiac (4) measurements to assess.

General sleep analysis is the smallest segment represented by Sleep quality determination (2) and sleep stage identification (2) - (see Fig. 9).

## *F. Level of Readiness, Environment Set up*

Lab environment: Over half of the work, with 59.1% (13), is dedicated to performing the experiments in the lab environments. This indicates the validation studies and lower-level technology readiness for transforming to the next level. This category is the most common environment for sleep monitoring.

Sleep lab: The second most represented category was specific sleep labs, which account for 22.7% (5). Like general lab environments, sleep labs are specialized facilities designed exclusively for sleep studies, offering a more focused setting for monitoring sleep-related disorders.

Home environment: Represented by 9.1% (2), reflected the growing trend of in-home sleep monitoring. The home environment setting allows for a more natural sleep experience for the individual being monitored. It indicates the advancements in user-friendly sleep monitoring technology with a higher technology readiness level, which has already gone through validation studies.

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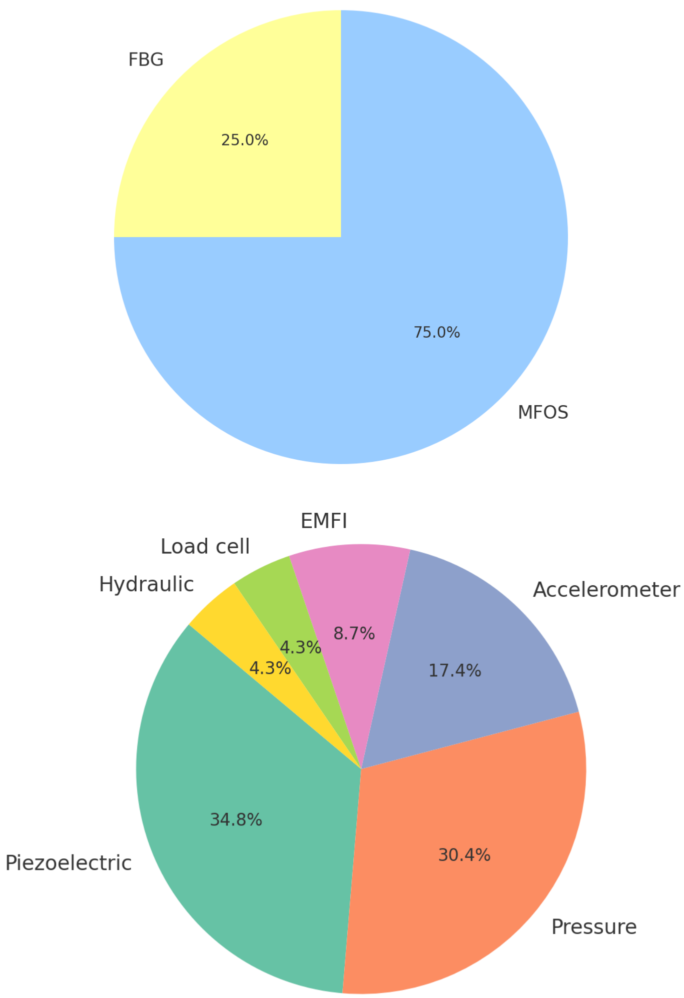


Fig. 4: Even though the number of sensor technologies under the category of traditional mechanical sensors is broader than fiber optic technology, our technology analysis shows a focus and interest in pressure sensors and piezoelectric sensors. We have observed an interesting approach of sensor fusion that might be a sign of an effort to improve the performance of the sleep monitoring system under this category despite the FOSs' emergence.

Clinical Trial: With 4.5% (1) referred to sleep monitoring conducted within the scope of research studies to evaluate the efficacy of interventions.

Community-dwelling older adults: With 4.5% (1), even though this category also could stand in the same with the home environment, due to the different setup and requirements, we have formed an independent category for it. It also indicates the focus on the elderly in their habitual residences, which can be important for studying sleep disorders prevalent in aging populations (see Fig. 10).

### G. Targets Groups

Our review revealed that 15 studies incorporated healthy individuals while seven involved patients as subjects in their experiments with sleep monitoring systems - one study recruited healthy individuals and patients. These figures are consistent with our lab environment analysis. Such individuals primarily validated the sleep monitoring system, indicating they had no known sleep disorders or associated health conditions.

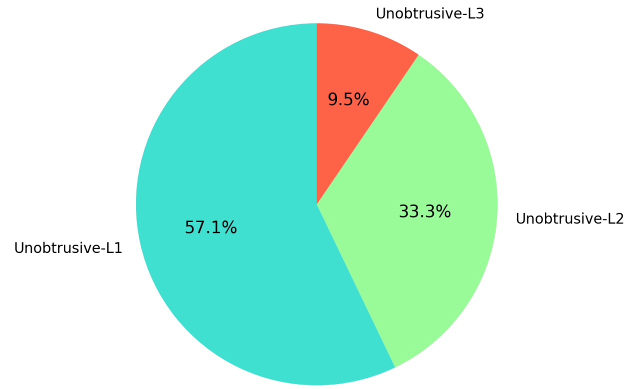


Fig. 5: Developing systems categorized under the unobtrusive L1 are more sophisticated regarding hardware development and signal quality; however, the largest portion falls in it. Sensor technology and signal processing advancements might highly influence this.

We classified the studies consists of patients into two primary categories: those with sleep disorders and other health conditions. Patients were further segmented within the sleep disorder group based on specific conditions. This subset encompassed three studies that focused on various forms of apnea, one study on patients experiencing sleep deprivation, and another on individuals with breathing disorders. The remaining two studies in the 'others' category included a diverse patient group recently discharged from hospital care and individuals diagnosed with cardiac conditions (see Fig. 11).

### H. Patent Output

Initially, 46 patents met the requirement criteria for further examination. After eliminating a significant number of patents available exclusively in Chinese and removing duplicate entries, the throughput analysis resulted in three remaining patents.

One identified patent [28] described a system where the BCG signal is measured using an array of piezoelectric sensors, with an additional pressure sensor proposed to detect the presence of a person on the mattress. The sensors are intended to be placed on the mattress. Another patent [29] involved a system designed to analyze sleep using one or more force sensors embedded in the mattress, with optional temperature and humidity sensors, although these additional sensors are outside the scope of this work. The third patent [30] detailed a system where sensors embedded in a small mat can be placed on top of the mattress and under the mattress topper or potentially under the mattress itself, using force or pressure sensors.

Many critical aspects, such as evaluation results and detailed signal processing techniques, are not well-documented in the

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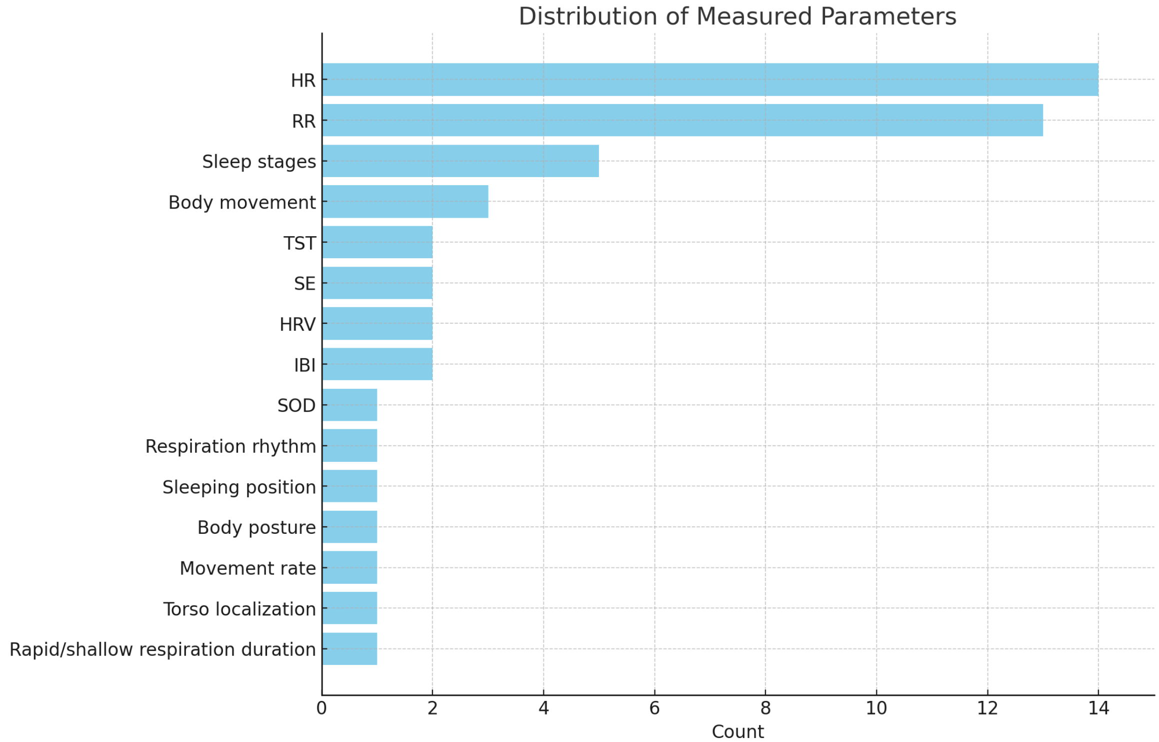


Fig. 6: Measuring cardiorespiratory parameters are meaningfully measured more frequently than the other parameters in sleep monitoring systems. This could be due to the wide applications of these parameters in general health and well-being, sleep-related and non-sleep-related parameters as well as sleep architecture.

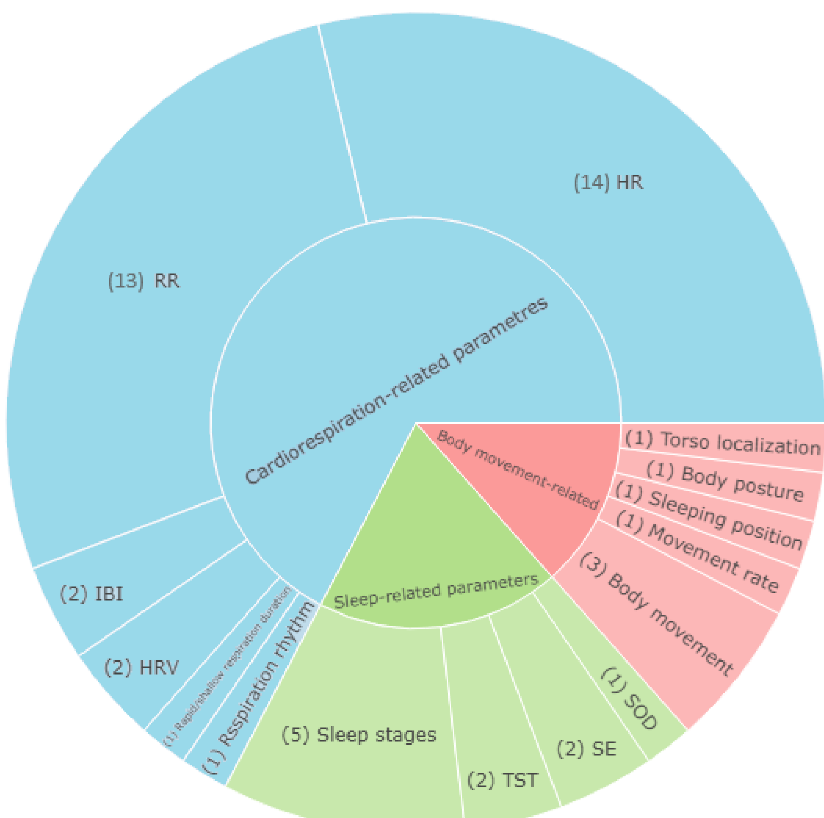


Fig. 7: 33 parameters out of 50 reported from the sleep monitoring systems are cardiorespiratory related. This is later considered as evidence of the disease-diagnosis tendency and application-oriented of the systems.


Fig. 8: The signal processing analysis shows that choosing the techniques depends on the application, signal, and system target group.

identified patents, making it challenging to include them comprehensively in the main body of this work.

## IV. Discussion

The number of publications meeting the defined criteria (21 papers) is adequate for statistically addressing and analyzing the issues. It should be noted, however, that the number of papers included in some borderline cases may lead to minor uncertainties in the conclusions. The review of sensor technology has shown that the sleep medicine field and the associated technology as the main focus is in the evolution state, and new developments are being demanded, which indicates the potential for further research.

### A. Current Trends in Sensor Technology

We first analyzed the fluctuations in the number of existing publications on mechanical and FOSs between January 2014 and May 2023 to recognize the general trends. We observed that the number of articles dealing with FOSs has increased since 2017, when this technology's first paper was published. Such a trend may reflect progressive enhancements in fiber optic technology, rendering it more conducive for sleep monitoring, coupled with a paradigm shift towards newer and more efficacious sensor technologies. In addition, new developments in this field aimed at providing a user-friendly, personalized, and precise system, appear to be driving the search for alternatives to classical mechanical sensors, leading to increased interest in FOS technology.

In 2023, FOSs witnessed a rise to a value of two, suggesting a recent innovation or increased acceptance. Our trend analysis indicated a consistent use of mechanical sensors, but their dominance might have been challenged by a growing interest in FOSs, as evidenced by the 2023 data point. Since the data was collected up to May 2023, the total number of publications is expected to be higher, while the proportion of different sensor technologies may remain similar. The intermittent data for FOSs may also indicate a technology in transition, potentially poised for growth in sleep monitoring and application extension.

We also explored the degree of unobtrusiveness, a crucial aspect of sensor technology. We observed a clear tendency toward developing least invasive systems by analyzing distri-

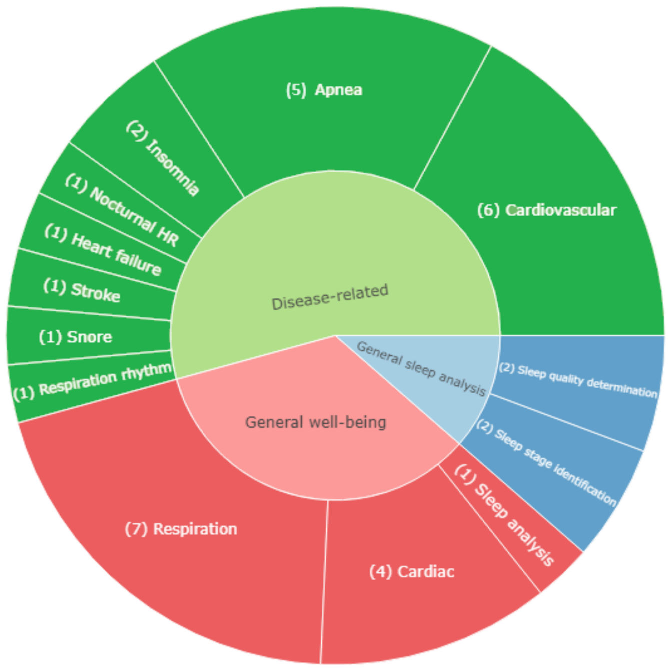


Fig. 9: The majority of the systems have a disease-related application, whether diagnosis or early detection of report of abnormalities (note: one system might have been designed to detect and diagnose more than one disease). This confirms the trend shift in sleep medicine from in-sleep lab diagnosis to in-home and continuous sleep monitoring.

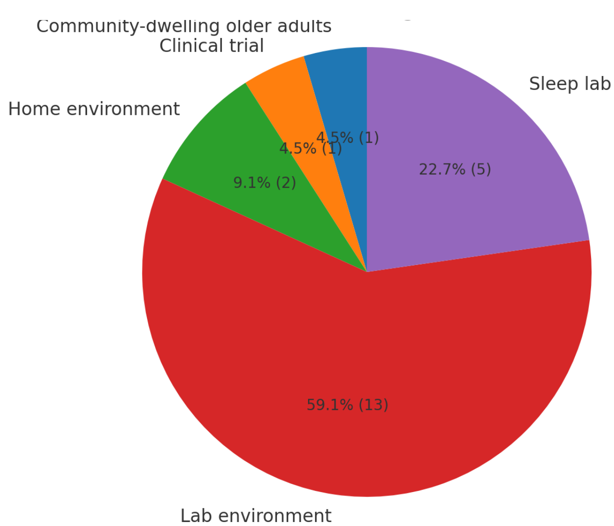


Fig. 10: We observed that despite the applications of the sleep monitoring systems, which are disease-related tendencies, the level of readiness needs to advance further to cope with the requirements.

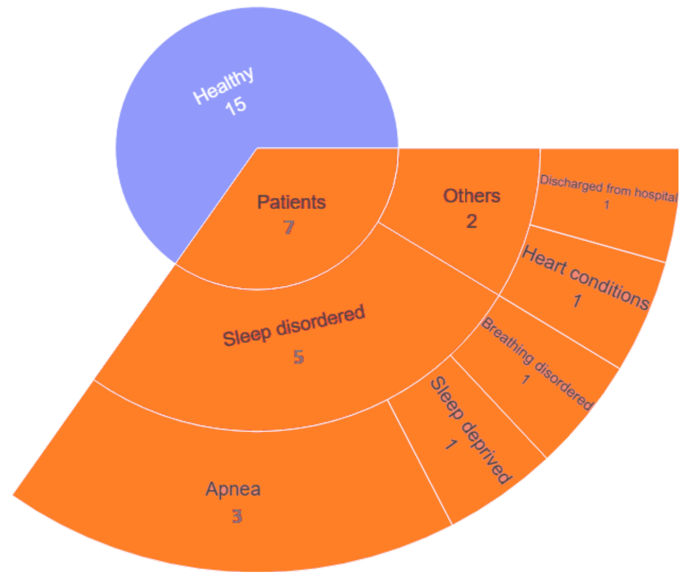


Fig. 11: Considering the different band of frequencies (e.g., cardiorespiratory parameters) in healthy individuals and patients, including the healthy subjects in the studies, indicates the level of readiness of the technology in which there are several stages to go through such that a system is reliably deployed for disease diagnosis. Note: one study includes both healthy individuals and patients.

butions across three levels. Approximately 60% of the publications achieved the highest level of unobtrusiveness, while fewer than 10% were categorized at the lowest level. This trend aligns with the shift in the development of new health monitoring technologies, prioritizing user or patient comfort. This is achieved by prioritizing minimally invasive sensors, underscoring a user/patient-centric approach to technological advancements.

Moreover, there are several sleep-tracking systems commercially available. The Beddit Sleep Monitor is designed to offer detailed insights into sleep patterns and quality by measuring HR, RR, snoring, room temperature, and humidity. This system analyzes the collected data to provide a comprehensive overview of sleep patterns. [31]. The Withings Sleep Tracking Mat, a pneumatic-based device placed under the mattress, monitors sleep parameters such as sleep cycles, HR, and snoring episodes, and can also detect breathing disturbances indicative of sleep apnea [32]. The Sleepace RestOn provides in-depth insights into an individual's sleep quality. It features a slim, soft belt that uses magneto-resistive sensing technology, placed directly on the mattress under the sheets, and measures sleep duration, HR, RR, body movements, and sleep cycles [33]. The Emfit QS offers detailed information about sleep quality, stress levels, and recovery, and is deployed under the mattress [34]. The Tempur-Pedic Sleeptracker, an AI-powered sensor layer that fits under a mattress, monitors various sleep stages, RR, and HR [35].

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TABLE I: The details of sleep monitoring systems developed using traditional mechanical sensors and FOSs. Note: LPF, SVM, KNN, IDFT, AMDF, DWT, ANN, CWT, and IEWT stand for low pass filter, support vector machine, k-nearest neighbor, improved discrete Fourier transform, average magnitude difference function, discrete wavelet transform, artificial neural network, continuous wavelet transform, and improved empirical wavelet transform, respectively.

| Paper | Year | Technology category | Technology specified | Parameters | Aim of system | Signal processing techniques | Performance evaluation |
|---|---|---|---|---|---|---|---|
| [36] | 2014 | Mechanical | Pressure | Sleep stages | General sleep analysis: Sleep stage identification | LPF, mean amplitude, mean frequency and variability, SVM, KNN, and Naive Bayes | Accuracy: SVM=70.33%, KNN=67.12%, Naïve Bayes=72.20% |
| [37] | 2014 | Mechanical | Piezoelectric | HR | Disease-related: Nocturnal HR | Moving average of the squared derivative of the movement, multichannel cepstra, sliding window Fourier transform, and spectral analysis | For 92.7% of the TST, the error is 1.06% and for HRs $>$ 100 bpm, the sensitivity is 28.4% |
| [38] | 2015 | Mechanical | Piezoelectric | IBI | Disease-related: Cardiovascular | DFT, IDFT, sliding window cepstrum, adaptive window autocorrelation (Corr), adaptive-window, AMDF, and Bayesian fusion | A BBI error of 2.2% for 68.7% of data with the possibility of analysis |
| [39] | 2015 | Mechanical | Pressure | RR, torso localization | General well-being: Respiration | The torso localization algorithm, adaptive threshold, and peaks detection | An overall error of 5.7% for a measurement duration of 10 minutes and an average of 160-180 breaths |
| [40] | 2016 | Mechanical | Accelerometer + Pressure | HR, RR, sleep/wake. | General sleep analysis and disease-related: Sleep quality determination and apnea | Spectral analysis, bi-directional recursive filter, simple derivative and threshold peak detection | For the Bland–Altman plot the mean HR difference is 0.076 Hz |
| [41] | 2017 | Mechanical | Piezoelectric | HR, RR, body movement, TST, sleep stages: sleep/wake | General sleep analysis | - | Accuracy: HR = 96.1%, RR = 93.3%, Correlation of TST (Sensor and PSG): r=0.87, sensitivity for awake epochs: 80.4%, sensitivity for sleep epochs: 92.5%, overall agreement is 90.5% for sleep stages |
| [42] | 2017 | Mechanical | Piezoelectric | HR, RR, movement rate, rapid and shallow respiration duration | Disease-related: Heart failure patients at risk for readmission | Random forest | NA |
| [43] | 2017 | Mechanical | Accelerometer + Pressure | RR | General well-being: Respiration | BPF and moving average | The average error (deviation) for both the accelerometer and the strip-type force sensor results are less than 250 ms. In 93.5% of the cases, the strip-shaped force sensor showed less than 100 ms deviation |
| [44] | 2017 | Fiber optic | MFOS | HR, RR | Disease-related: Apnea detection, stroke and cardiovascular | DWT, 3rd order polynomial Fit, Savitzky-Golay smoothing | An average error of HR=0.55±0.59 bpm and RR=0.38±0.32 bpm (mean ± standard deviation) |
| [45] | 2020 | Mechanical | Piezoelectric | RR, HR, body movement, TST, SE | General well-being: Cardiorespiration and Sleep analysis | MUSIC | The correlation and deviation of RR are r = 0.99 and 0.2 cycles per minute (cpm), respectively |
| [46] | 2020 | Mechanical | Piezoelectric | Sleeping position, body movement, HR, RR | Disease-related: Insomnia | ANN | Accuracy: 91.8% for sleeping position and motion and 86% for no bed occupancy, wakefulness, non-REM sleep and REM sleep |

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TABLE II: The details of sleep monitoring systems developed using traditional mechanical sensors and FOSs (continued). Note: MOD, LOA, and QB stand for mean of difference, limit of agreement, and quiet breathing, respectively.

| Paper | Year | Technology category | Technology specified | Parameters | Aim of system | Signal processing techniques | Performance evaluation |
|---|---|---|---|---|---|---|---|
| [47] | 2020 | Mechanical | Pressure | RR, body posture | General well-being: Respiration | Multi-sinusoidal model based, extended Kalman filtering, Welch power spectrum density, and third order Chebychev BPF | Maximum deviation of RR: 1.93 bpm |
| [48] | 2020 | Fiber optic | MFOS | HR, RR | Disease-related: Apnea detection | Adaptive histogram-based thresholding, DWT, sliding window | Accuracy of 49.96%, sensitivity of 57.07%, specificity of 45.26%, normalized mean absolute error for HR: 5.42% and RR: 11.42% |
| [49] | 2021 | Mechanical | EMFI | SE, SOD, and sleep stages, HR, RR, body movements | General well-being and sleep analysis | NA | NA |
| [50] | 2021 | Mechanical | Hydraulic | HR | Disease-related: Cardiovascular disease | Bi-LSTM and sixth order Butterworth BPF | HR error: 0.47 bpm |
| [51] | 2021 | Mechanical | EMFI + load cells | HR, IBI | Disease-related: Cardiovascular disease | Bandpass, moving average, and least squares linear regression | NA |
| [52] | 2022 | Mechanical | Accelerometer + Pressure | HR, RR, sleep stages | General well-being and disease-related: Apnea and Insomnia | Second-order LPF, Hanning window, and FFT spectrum | Accuracy: HR 1.5 bpm, RR 0.7 bpm, 97.2% snoring recognition, sleep stage recognition: 95.1% |
| [53] | 2022 | Mechanical | Piezoelectric | HRV | Disease-related: Cardiovascular and sleep snore | 200-order FIR, multi-instance learning | Correlation between BCG and ECG of HRV and parameter mean is: correlation coefficient r=1.00 and p value=0.61 |
| [54] | 2023 | Fiber optic | MFOS | HR, HRV | Disease-related: Cardiovascular | CWT, Bi-LSTM | Median error BBI: 4.4 ms |
| [55] | 2023 | Fiber optic | FBG | HR | General well-being and disease-related: Cardiorespiratory measurements, apnea and tachypnea | First-order Butterworth, Welch estimator (power spectrum density) | Bland–Altman analysis of HR: MOD values close to 0 and LOAs values lower than 3.6 bpm for T and 2.0 bpm for QB, and LOAs up 2.6 bpm for QB + T |
| [56] | 2023 | Mechanical | Piezoelectric | Respiration rhythm, RR | Disease-related: Respiration rhythm | IEWT | Absolute error: 0.003 Hz, precision: 98.31%, 93% of RIs were correctly detected (within MEAN ± 1.96SD)) |

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### B. Advancements in Sensor Technology Application

However, not only the sensor technology itself but also the application and purpose of the system are of major interest and have been extensively analyzed. Several different applications are possible depending on the parameters that can be measured with the sensor system.

More frequent monitoring of the cardio-respiratory parameters was identified as a main target of the systems (HR: 14 and RR: 13). This observation correlates with the fact that these vital signs are considered as one of the most relevant and contributing parameters to health-related characteristics and disorders which confirms the identification of cardiovascular diseases as one of the leading causes of death [57]. Furthermore, cardiac and respiratory signals can be used for further analysis and subsequent determination of other health or sleep-related parameters/disorders such as SE, sleep stages, or sleep apnea, even if these characteristics were not directly addressed in the studies. This leads us to conclude that future development will continue to be in the direction of acquiring these crucial physiological signals with a concentration on improving the measurement's accuracy, reliability, and consistency. This, in parallel, puts the development of advanced signal processing techniques and algorithms for further processing on the focus. Furthermore, as observed in some studies, there is an expectation to measure additional cardiac parameters, such as blood pressure, to gain deeper insights into the cardiac cycle.

We also noticed that the total range of measured parameters is relatively broad, which indicates the variety of possible sensor applications. This, in turn, reflects the trend toward individualization of healthcare systems, where the measurement of numerous parameters creates a comprehensive picture of a person's state of health that is unique to each individual.

The variety of parameters that can be measured is, among other things, the result of a wide range of signal processing and subsequent signal analysis methods. This variety of methods shows that the field is still evolving and that none of the methods has taken a dominant position.

Regarding the fields of application, the predominance of disease-related use (18 cases) can be explained by the fact that research is driven by practical implementation. By focusing on the medical field, the research sees the already known specific diseases and strives for a faster transfer into practice with clear results that could support the medical staff.

### C. Level of Readiness and Related Characteristics

It is also important to acknowledge that, despite the aim of practical application, the readiness level remains relatively low. This is indicated by 59.1% of the developments have only been tested in a laboratory setting. This observation confirms the previous statement on the evolving field, trend shift, and potential for new developments. With appropriate evaluation phases, new advancements can pave the way for personalized medicine.

The fact that most studies focused on healthy subjects suggests that most systems are still in the preliminary stages of development. Evaluating technologies in healthy individuals usually represents the initial phase, whereas deploying these systems in patients with diseases generally demands a more advanced stage of development. However, it is important to note that in the case of advanced development, where the products are (almost) ready for the market, and companies drive the research and evaluation, the results are not necessarily published to maintain corporate secrecy and not jeopardize a market launch and subsequent commercial use.

During the information collection process, it was evident that the level of descriptive detail of methods, studies, and results varied significantly from one article to another. This led to a situation where statistical analysis could not be performed for some aspects because of the lack of relevant data. Nonetheless, the information may interest the scientific community, and we will address some of these issues in the following.

### D. Evolution and Effect Using Mechanical/Fiber Optic Technology

Data storage and transmission, for instance, is a major concern, particularly regarding data security and user privacy. In total seven systems reported on this aspect, of which five used WiFi for long-range data transmission ( [42], [48], [47], [49], [53]) and two used Bluetooth Low Energy (BLE) ( [43], [52]) for short-range transmission of the data. Well-establishment, stability, accessibility, and popularity of these transmission protocols could be the main reasons for their deployment. In addition, since some of the devices utilize the strategy of on-system local data storage, the data does not necessarily need to be transmitted in real-time, simplifying the use of BLE. This could be another indicator that as many of the systems are at an early stage of development, no data transmission has been implemented, yet. The acquired data is stored exclusively locally on the device and then manually delivered to a computing device for processing ( [38], [44]).

A system's cost and final expense could be another key factor, particularly for the end user. The increasing level of readiness and preparation for the in-home operational system is often a long-term procedure. Therefore, estimating the expense of a system at an early stage is usually a challenge. Hence, the cost factor was not discussed in detail in the articles, although in one of the publications, the emphasis was put on a low-cost solution, which, however, due to the missing cost calculation, does not provide exact data [46]. For the same reason, no information about certification was provided since the certification process typically occurs at a later stage of development. An exception is [38], which states that the safety assessment test of the BedS prototype device has been approved according to the IEC-60601-1 standard.

The observed trend of increased use of fiber optic technology in recent years prompts whether changes in application areas, processing methods, and other aspects related to this trend are evident and, more particularly, whether this resulted in any associated beneficial aspects.

In this regard, we have observed that systems using fiber optic sensors often have a higher level of technology readiness in terms of evaluation in a sleep laboratory or clinical trial.

For example, out of a total of five applications in the sleep laboratory, one [48] was performed with fiber optic technology. Moreover, the only system evaluated in a clinical trial used fiber optic-based sensor [44]. In summary, 50% of the developments using fiber optic technology were tested in an environment requiring a higher level of readiness (i.e., sleep lab or clinical trial), significantly greater than mechanical sensors. Due to the limited evidence available, no definitive conclusion can be drawn as to the exact causes of this discrepancy. However, higher accuracy of measurements with fiber optic technology and more frequent use of this type of sensor by larger and more experienced research groups or companies due to the higher cost compared to traditional mechanical sensors could be the possible reasons. Consequently, this also means that a more sophisticated evaluation (e.g., in a sleep laboratory or a clinical trial) is possible due to the greater resources available.

There is also a significant difference in the level of unobtrusiveness - while only about 50% of traditional mechanical sensors reached the Unobtrusive-L1 level, it was 100% for fiber optic-based systems. One possible reason for this is that the higher accuracy of the measurement allows the sensors to be placed further away from the person, potentially increasing the level of unobtrusiveness.

Another distinctive point is that the systems developed using fiber optic technology very often (in three out of four systems) also detect a specific sleep disorder - sleep apnea - in addition to the heart and respiratory signals. In the case of traditional mechanical sensors, only two out of 17 systems have focused on sleep apnea detection. This draws attention to the quality of the signals measured with fiber optic sensors and the associated signal processing techniques that allow an efficient assessment of the RR and additional respiratory characteristics, such as e.g., volume, which is crucial for detecting sleep apnea.

Overall, the reported accuracy of measurements of heart and respiratory signals with the fiber optic-based systems remains consistently high (e.g. Mean Average Error (MAE) of $0.55 \pm 0.59$ for HR and $0.38 \pm 0.32$ for RR in [44]), While the variability of accuracy is significantly higher with traditional systems (e.g. MAE of 1.42 bpm in [50]). This provides us with preliminary evidence that fiber optic technology allows a constantly high level of precision and can at least reach the level of the highest-performing mechanical sensors or even exceed them in some cases. However, the data on the performance of the examined systems contained in the reviewed articles exhibit considerable differences in completeness, comprehensiveness, and accuracy.

## V. Conclusions

In this work, we noticed a shift towards using FOSs, with the ratio of FOSs to mechanical sensors improving from 1:8 during 2014-2017 to 1:3 in 2020-2023. This shift can be attributed to the (1) enhanced unobtrusiveness of FOSs compared to traditional mechanical sensors (all FOS-based systems were classified at the highest level of unobtrusiveness) and (2) the accuracy of FOS systems have also seen considerable improvements, evidenced by their exclusive use in clinical trials - both are affected by signal quality. The technology readiness appears to be in its early stage, evidenced by (1) the evaluation of four systems in sleep labs and only one in clinical trials and (2) the predominant application of the systems reported in disease-related diagnosis, contrasting with the recruitment of primarily healthy subjects. Nonetheless, the single study in clinical trials with an FOS-based system highlights their potential for future studies. Despite these advantages, the cost of FOS systems remains a significant barrier, prompting concerns among end-users regarding affordability. This could be inspired by exploring the traditional mechanical sensors, potentially in fusion setups, as a cost-effective alternative that does not compromise the accuracy and reliability necessary for critical applications. While FOS technology is a significant step forward in sensor technology with its unobtrusiveness, accuracy, and application, its currently higher cost than traditional sensors presents a challenge and approach to selecting sensor technologies based on application-specific requirements and cost considerations, particularly in continuous in-home monitoring.

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