



Review

# Unobtrusive Monitoring of Sleep Cycles: A Technical Review

Juwonlo Siyanbade<sup>1</sup>, Bessam Abdulrazak<sup>1,\*</sup> and Ibrahim Sadek<sup>1,2,\*</sup>

<sup>1</sup> AMI-Lab, Computer Science Department, Faculty of Science, University of Sherbrooke, Sherbrooke, QC J1K 2R1, Canada; siyanbade.juwonlo@usherbrooke.ca

<sup>2</sup> Biomedical Engineering Department, Faculty of Engineering, Helwan University, Cairo 11792, Egypt

\* Correspondence: bessam.abdulrazak@usherbrooke.ca (B.A.); ibrahim\_ibrahim@h-eng.helwan.edu.eg or ibrahim.sadek@usherbrooke.ca (I.S.)

**Abstract:** Polysomnography is the gold-standard method for measuring sleep but is inconvenient and limited to a laboratory or a hospital setting. As a result, the vast majority of patients do not receive a proper diagnosis. In an attempt to solve this issue, sleep experts are continually looking for unobtrusive and affordable alternatives that can provide longitudinal sleep tracking. Collecting longitudinal data on sleep can accelerate epidemiological studies exploring the effect of sleep on health and disease. These alternatives can be in the form of wearables (e.g., actigraphs) or nonwearable (e.g., under-mattress sleep trackers). To this end, this paper aims to review the several attempts made by researchers toward unobtrusive sleep monitoring, specifically sleep cycle. We have performed a literature search between 2016 and 2021 and the following databases were used for retrieving related articles to unobtrusive sleep cycle monitoring: IEEE, Google Scholar, Journal of Clinical Sleep Medicine (JCSM), and PubMed Central (PMC). Following our survey, although existing devices showed promising results, most of the studies are restricted to a small sample of healthy individuals. Therefore, a broader scope of participants should be taken into consideration during future proposals and assessments of sleep cycle tracking systems. This is because factors such as gender, age, profession, and social class can largely affect sleep quality. Furthermore, a combination of sensors, e.g., smartwatches and under-mattress sleep trackers, are necessary to achieve reliable results. That is, wearables and nonwearable devices are complementary to each other, and so both are needed to boost the field of at-home sleep monitoring.

**Keywords:** ballistocardiography; sleep cycles; contactless monitoring; home monitoring



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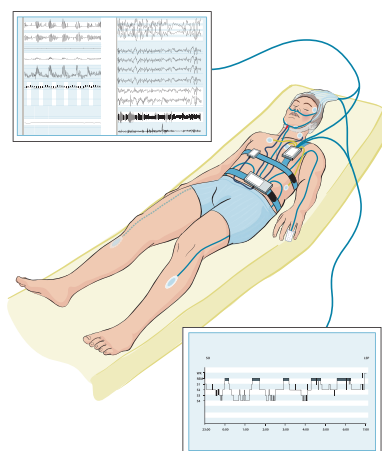
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## 1. Introduction

Sleep is important for the physical and mental well-being of an individual. The quantity and quality of sleep are generally associated with chronic diseases and health risks such as diabetes, cardiovascular diseases, renal failure, anxiety, and depression [1,2]. The fast pace of modern society and the rapid increase in the aging population have contributed to the population of people being affected by sleep disorders. The Centers for Disease Control and Prevention (CDC) reported that a third of the United States population does not get enough sleep [1]. A similar statistic was reported by the Canadian Men's Health Foundation (2016) stating that 30% of Canadian men are sleep deprived. This is reflective of the global populace as sleep disorders are rapidly becoming a global concern, leading to a range of societal problems [3]. Sleep monitoring is important and could be a lifesaver for people with undiagnosed sleep disorders [4,5]. A major motivation for sleep monitoring is the effect it has on health and well-being [6]. However, the process requires trained sleep technicians to perform polysomnography (PSG).

The PSG is the medical gold standard for sleep studies. It uses various intrusive sensors to record multiple physiological signals during sleep, namely electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), electrocardiogram (ECG), body position,

ronasal airflow, photoplethysmogram, abdomen, and thorax respiratory efforts, and others (Figure 1).

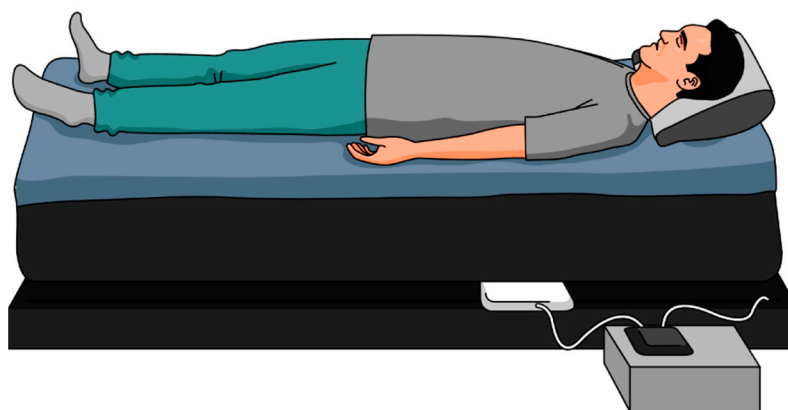


**Figure 1.** An illustration showing the several sensors attached to a monitored individual during an overnight PSG study.

It is a fairly inconvenient, time-consuming, and expensive technique, used only clinically, and cannot be used for longitudinal sleep tracking [7,8]. The PSG protocol can itself affect the quality of sleep because of unfamiliarity with the environment and the multiple attachments used in the study. The results from the study (sleep score) include sleep onset latency, sleep efficiency, and sleep stages. The structure of sleep includes various stages characterized by specific physiological changes. These stages are Wake, Non-Rapid Eye Movements (NREM), and Rapid Eye Movement (REM), i.e., Wake (“wakefulness before sleep”), NREM1 or N1 (“very light sleep”), NREM2 or N2 (“light sleep” defined by EEG recordings), NREM3 or N3 (“deep sleep”), and REM (“dream state”) [9]. The transition from one stage to the next is described as the sleep cycle.

Due to the complexity of PSG, other methods have been proposed as alternatives. Actigraphy (ACT) and photoplethysmography (PPG) are two solutions that enable long-term monitoring and produce a valid assessment of sleep/wake behavior. Metrics derived from longitudinal sleep tracking can help detect and manage various diseases, e.g., cardiorespiratory disorders and dementia [10]. That is, the collection of longitudinal sleep data on a large scale can boost epidemiological studies that examine the influence of sleep on health and disease [11]. There are also less cumbersome approaches to sleep monitoring owing to the advancement, adoption, and integration of technology into healthcare in the form of non-contact systems, wearables, and mobile systems [11–15]. These systems capitalize on the strong correlation between bio-vital signs and sleep.

Researchers have been focusing on creating non-contact sleep tracking methods (e.g., under-mattress sleep trackers shown in Figure 2) that can achieve closer outcomes to PSG [16]. These systems can potentially be used for sleep-quality monitoring. Examples include systems working on the principle of ballistocardiography (BCG) (Sadek et al. [17]), strain gauge (Lima et al. [18]), seismometer (Li et al., 2018), ultrasonic (Hsu et al., 2017; Tran et al., 2019), ultra-wideband system (Kang et al., 2020), RF signals (Liu et al. [4]), fiber optics (Koyama et al. [19]), and smart textiles (Zhou et al. [20]).



**Figure 2.** An illustration showing the positing a contactless sensor under the mattress of a monitored individual.

To this end, several devices and algorithms have been suggested, presented, and implemented, but fewer for sleep-cycle monitoring which is an important aspect of sleep. As a result, this paper aims to review existing works on sleep-cycle monitoring using unobtrusive sensors. The rest of the paper is organized as follows. Sections 2 and 3 presents the methodology used in the literature selection. Discussion and opinions are presented in Section 4. Lastly, the paper is concluded in Section 5.

## 2. Methodology

For this review, the literature search was performed using a systematic computerized approach: IEEE, Google Scholar, Journal of Clinical Sleep Medicine (JCSM), and PubMed Central (PMC). The keywords used to retrieve publications were chosen based on common terms used in the field, from the topic under review, and database suggestions (Appendix A). Due to the number of results from the search on Google scholar (2810), sleep-cycle monitoring using contactless sensors research cannot be exhaustively reviewed. Therefore, only studies between 2016 and 2021 (1730) were considered. The titles and abstracts of the articles were screened, and references from relevant articles were scanned for other relevant publications. Articles included in the review were read and evaluated. Other conditions for inclusion were implemented tools, presentation of a method to measure sleep stage, studies published in a scientific journal or a scientific conference, studies with participants or clinical population, and studies with validation. A table showing the overview of the 14 reviewed publications is presented in Table 1.

**Table 1.** Brief description of the literature covered in the review.

Study	Objective	Mode of Monitoring	Subjects	Validation Method	Evaluation/Result
Nam et al. (2016) [21]	Monitoring sleep quality using vital signs.	Tri-Axial Accelerometer and Pressure Sensor	10	Validated with PSG and video camera	<ul style="list-style-type: none"> <li>✦ The results showed that the proposed method can measure vital signs affecting sleep quality.</li> <li>✦ The estimators of the sleep quality equation were consistent with reference signals.</li> </ul>
Nguyen et al. (2016) [22]	Presenting a lightweight and inexpensive wearable sensing system.	LIBS	8	Validated with PSG	<ul style="list-style-type: none"> <li>✦ The system produced comparable accuracy with PSG for sleep stages classification.</li> </ul>

Table 1. Cont.

Study	Objective	Mode of Monitoring	Subjects	Validation Method	Evaluation/Result
Gu et al. (2016) [23]	Detecting transition between sleep stages for sleep quality monitoring and intelligent wake-up call.	Mobile service–Sleep Hunter	15	Validated with existing actigraphy-based products, Zeo and Jawbone Up	✦ Testing the data over one month provided that the detection accuracy of Sleep Hunter was 64.55%.
Tal et al. (2017) [24]	Validating the efficacy of the system for detecting sleep/wake state and sleep parameters against PSG. Testing if the system can detect sleep architecture in various sleeping conditions.	EarlySense system made up of piezoelectric sensor and a mobile application	63	Validated with PSG	✦ Relative to PSG, the system showed sleep detection sensitivity, specificity, and accuracy of 92.5%, 80.4%, and 90.5%, respectively.
Guettari et al. (2017) [25]	Detecting the presence of a person in bed and producing an estimation of the sleep quality.	Thermopile sensor	13	Validated with PSG	✦ The obtained evaluation results have shown 87% of good classifications with 95% confidence intervals for recognition of the three deducted stages.
Seba et al. (2017) [26]	Validating the use of a thermal radiation sensor as a sleep analysis sensor. Analyzing physical activity and thermal radiation during sleep.	Thermopile sensor, thermal camera, accelerometer, iButton	1	Connected to an acetimeter consisting of an inertial unit fixed on the wrist of the patient	✦ The study validated the efficacy of using temperature sensors for the extraction of skin temperature, actimetry, and the presence, absence, and position of a patient in a bed.
Zambotti et al. (2017) [27]	Comparing the output of a multi-sensor sleep tracker (ÖURA ring) to PSG for measuring sleep and sleep phases.	ÖURA ring	41	Validated with PSG	✦ The ÖURA ring showed good agreement with the PSG measurements of total sleep time, sleep onset latency, and wake after sleep onset.
Zambotti et al. (2018) [28]	Comparing the performance of a consumer multi-sensory wristband (Fitbit Charge 2) in measuring sleep stage classification versus PSG.	Fitbit Charge 2	44	Validated with PSG	✦ Fitbit achieved 82% accuracy in sleep cycle classification. It overestimated total sleep time and “light sleep” but it underestimated sleep onset latency and “deep sleep”.
Pallesen et al. (2018) [29]	Validating the impulse radio ultra-wideband pulse-doppler radar technology against PSG for sleep assessment.	Novelda XeThru radar	12	Validated with PSG	✦ The mean values obtained for accuracy, sensitivity, specificity, and Cohen kappa were 0.931, 0.961, 0.695, and 0.670, respectively.

Table 1. Cont.

Study	Objective	Mode of Monitoring	Subjects	Validation Method	Evaluation/Result
Tuominen et al. (2019) [30]	Validating the accuracy of a BCG Beddit Sleep Tracker (BST) for sleep monitoring.	Beddit Sleep Tracker	10	Validated through comparison with PSG	<ul style="list-style-type: none"> <li>❖ BST was able to identify sleep onset latency with some accuracy. However, it underestimated wake after sleep onset and overestimated total sleep time and sleep efficiency.</li> <li>❖ BST did not distinguish between NREM stages and did not detect the REM stage.</li> </ul>
Kalkbrenner et al. (2019) [31]	Assessing a novel type-4 monitoring system for automated sleep staging.	Type-4 monitoring system	53	Validated with PSG	<ul style="list-style-type: none"> <li>❖ The system provided satisfactory results for three-stage sleep classification with an accuracy of 76.3% and Cohen's kappa of 0.42.</li> </ul>
Lautslager et al. (2020) [32]	Assessing the performance of a radar-based system for sleep staging performance.	Circadia Contactless Breathing Monitor (model C100)	9	Validated with PSG	<ul style="list-style-type: none"> <li>❖ The system produced an overall accuracy of 66.7%.</li> </ul>
Zhang et al. (2021) [33]	Present the model, design, and implementation of SMARS, a sleep monitoring system based on ambient radio signals.	Ambient radio signals	6	Validated with PSG and Four state-of-the-art RF-based respiratory monitoring systems	<ul style="list-style-type: none"> <li>❖ Accuracy of 88.4% for three-stage classification, coverage of up 8–10 m, and detection rate of 80%.</li> </ul>
Yu et al. (2021) [15]	Presenting a Wi-Fi-Sleep, a sleep stage monitoring system to monitor and classify sleep.	Wi-Fi transceivers	12	Ground truth was obtained from PSG. The performance was Validated with SMARS and RF-Sleep	<ul style="list-style-type: none"> <li>❖ Wi-Fi-Sleep showed 81.8% accuracy for four-stage sleep classification.</li> </ul>

### 3. Literature Review

Nam et al. [21], proposed a system based on a tri-axial accelerometer and a pressure sensor to quantify sleep quality. The system was able to monitor the sleeping position, non-REM sleep time, movement, heart-rate variability (HRV), and variations in the breathing amplitude (i.e., an estimate of the presence and number of apneic episodes). The sleeping posture was determined using a wearable sensing belt integrating the tri-axial accelerometer. The wake–sleep period was determined via respiratory signals obtained through the bed pressure sensor. Ten volunteers (nine males and one female) participated in the experiments, and the system was validated against the PSG and a digital video camera. The authors managed to determine sleep quality based on three parameters (i.e., non-REM sleep time, the number of apneic episodes, and the total duration of the subject's dominant sleeping pose). At last, the estimated sleep quality was found to be consistent with reference devices.

Nguyen et al. [22] presented a prototype of their Light-weight In-ear BioSensing (LIBS) system that can be used for staging a whole-night sleep study. The system was placed inside the ear canal to continuously record electroencephalogram (EEG), electrooculogram (EOG), and electromyogram (EMG) signals representing electrical activities of the human brain, eyes, and muscles. The overlapping features (i.e., temporal, spectral, and non-linear)

of the signals were separated by a non-negative matrix factorization (NMF)-based model to match the reference signals obtained from PSG. LIBS was tested on eight participants (three females and five males) and PSG recordings were acquired in parallel. On average, the system achieved 95% accuracy for sleep-stage classification. The classification accuracy was 87% for NREM1, 89% for NREM2, and 78.31% for REM. Besides, the sensitivity was 80% and 83% for NREM1 and REM, respectively. Considering how the system was worn, the users took a survey, and it was concluded that 85.8% agreed that LIBS did not disturb their sleep.

A mobile service (i.e., Sleep Hunter) for sleep quality monitoring and smart wake-up calls that detect transitions between sleep phases was introduced by Gu et al. [23]. For sleep-stage detection, Sleep Hunter employed a statistical model denoted as the linear-chain conditional random field (CRF). It used sensors installed in smartphones to monitor body movements, acoustic events, ambient lighting conditions, sleep length, and personal factors. At various stages of sleep, a smartphone placed next to the pillow will detect body movements such as rollover, leg stretching, and leg jerking. Sleep data were collected from 45 volunteers to train the CRF model, and the system was tested on 15 participants (eight males and seven females) for a month. Sleep Hunter was compared to other actigraphy-based technologies, Zeo and Jawbone Up, to validate its performance. The detection accuracy in a three-stage classification was 64.55%. The system was also capable of providing smart wake-up services based on sleep stage detection. The user can set a one-hour time frame when they want to be woken up, and the device will wake them up if it detects a light sleep stage within that time frame; otherwise, it will wake them up at the end of the hour.

Tal et al. [24] conducted experiments to validate a contact-free monitoring system (EarlySense) made up of a piezoelectric sensor and a mobile application. The goals of the study were to verify the accuracy of the system in assessing sleep/wake state and sleep parameters as compared to PSG, as well as to see if the system can detect sleep architecture in different sleeping situations, such as when another person is in bed. The pressure-based device was placed under the mattress around the chest region to measure the respiratory rate, heart rate, and sleep stage. The results obtained from 63 (45 males and 18 females) participants produced comparable results with PSG for the total sleep time (TST), wake, REM, and non-REM. EarlySense produced 96.1% and 93.3% accuracy of continuous measurement of heart rate (HR) and respiratory rate (RR). The sleep detection sensitivity, specificity, and accuracy were 92.5%, 80.4%, and 90.5%, respectively.

The research by Guettari et al. [25] was aimed at detecting the presence of patients in bed and estimating their sleep quality. A thermopile sensor producing thermal signals was fixed on the wall to achieve this goal. The Symbolic Aggregate Approximation (SAX) method was implemented in thermal signal segmentation processing. The SAX method created each segment by first segmenting the mid-variance and then determining its sleep phase. The system extracted the length of each thermal data segment, the variance of each segment's thermal segment, and the level of each segment. The Kohonen self-organized map (SOM) was used to classify the signal segments into three sleep phases: deep sleep (R, N3), light sleep (N1, N2), and wake phase (W). The number of phases was fewer than professional systems, but the system was efficient for long-term monitoring. Further work is being carried out to improve the classification. Based on the 13 patients (nine males and four females) who took part in the study, the obtained classification results showed an accuracy of 87% with 95% confidence intervals for the recognition of the three sleep stages.

A new approach for sleep analysis was developed and presented by Seba et al. [26]. In this approach, sleep activity was classified into three stages based on thermal signature: waking, relaxed sleep, and restless sleep. This device, which was based on temperature monitoring (both patient and ambient), was integrated into the framework of the Smart-EEG project by the SYEL—SYstèmes ELectroniques team. The system was made up of a thermopile sensor TMP007, a thermal camera, an accelerometer, and an iButton. The thermal camera was placed on the wall, the thermopile sensor was placed on a frame above



the subject, and the iButton was worn on the wrist. The sensor was used to determine the temperature of the upper “bed + patient” region. Images from the thermal camera in medical format gave information that could be analyzed by experts to understand postural changes and changes in temperature measurement relating to the upper part of the “bed + patient” and the ambient environment. An inertial unit was used to obtain wrist acceleration in three axes to evaluate the responses of the thermopile sensor. iButtons were used to autonomously test the temperatures of the wrist, distal, and proximal skin. It was observed that there was a relationship between the day/night alternation, wake/sleep alternation, and high and low temperature. The temperature of the body drops during sleep and rises during the day, while skin temperature rises during sleep and falls during waking hours. The classification for calm and restless sleep was carried out using the acceleration module. In sum, this study validated several studies linking body temperature to sleep.

De Zambotti et al. [27] carried out a comparison of a multi-sensor sleep tracker (ÖURA ring) with PSG in terms of measuring sleep and sleep phases. ÖURA ring is capable of detecting the pulse rate, variation in inter-beat-intervals (IBIs), and pulse amplitude from the finger optical pulse waveform. It also measures motion and body temperature and with machine learning methods, it can calculate and classify sleep into stages. The study was aimed at validating the accuracy of these functionalities. Sleep data were collected from the 41 participants (28 males and 13 females) recruited for the exercise by both the ring and PSG. The ÖURA ring showed good agreement with the PSG measurements in terms of TST, SOL, WASO, and light sleep (N1 + N2). However, the ring overestimated REM and underestimated “deep sleep” (N3). Epoch-by-epoch (EBE) analysis showed that it had a high sensitivity for detecting sleep (95.5%), 65% for detecting light sleep, 51% for detecting deep sleep, and 61% for detecting REM sleep, but low specificity in wake detection (48%). Furthermore, the accuracies of classifying PSG-defined TST ranges of (<6 h, 6–7 h, >7 h) were 90.9%, 81.3%, and 92.9%, respectively.

In another validation study by de Zambotti et al. [28], the authors assessed the performance of a consumer multi-sensory wristband (Fitbit Charge 2) for sleep-stage classification versus PSG. The Fitbit device can monitor time spent awake, light sleep, deep sleep, and REM sleep, in addition to sleep/wake states. Forty-four subjects (18 males and 26 females) participated in the study, during which participants wore a Fitbit on their wrist while undergoing PSG. The data captured from the systems were compared using t-tests, Bland–Altman plots, and epoch-by-epoch (EBE) analysis. The result from Bland–Altman plots showed that Fitbit overestimated TST and “light sleep” (N1 + N2) while it underestimated SOL and deep sleep (N3). There were, however, no significant differences in the recordings for the wake after sleep onset and time spent in REM sleep. Based on the EBE analysis, Fitbit had accuracies of 96% in detecting sleep (sensitivity), 61% in detecting PSG wake (specificity), 81% in detecting “light sleep”, 49% in detecting “deep sleep” and 74% in detecting REM sleep. Overall, Fitbit achieved 82% accuracy in sleep cycle classification.

Pallesen et al. [29] conducted a pilot study to validate IR-UWB pulse-doppler radar technology against polysomnography (PSG) for sleep assessment. UWB technology uses short-range radio waves with very low energy levels. This technology is based on the idea that body, limbs, and breathing motions trigger shifts in the frequency (Doppler shift) of radio waves. Twelve volunteers (six males and six females) were assessed overnight by a Novelda XeThru radar and PSG. Comparisons between bedtime and wake-up time were made using the respiratory signal. The result of the study showed the mean differences between the radar parameters and PSG estimates for SOL, WASO, and TST. The mean values obtained for accuracy, sensitivity, specificity, and Cohen kappa were 93.1%, 96.1%, 69.5% and 67%, respectively. The findings indicated that IR-UWB radar could be an alternative objective measure to actigraphy. The ability to assess movements from several parts of the body simultaneously, such as movement from the extremities and respiration movements, which both shift significantly during sleep, is an obvious advantage over actigraphy. It was also indicated that the presence of more than one person in the bed will

affect the reading, as the system was unable to differentiate between movements caused by different individuals.

A validation study was carried out by Tuominen et al. [30] to assess the accuracy of the BCG Beddit Sleep Tracker (BST) for monitoring sleep. Ten participants (five males and five females) were recruited for the test and data from PSG, BST, and other technologies were collected for two nights. Analysis showed that BST was able to identify SOL. However, the system underestimated wake after sleep onset and overestimated TST and sleep efficiency. There was also a poor outcome for sleep classification as BST failed to differentiate between NREM stages and did not detect the REM stage. It was concluded that further research and development work in sleep tracking devices is still required, as well as more validation studies for other emerging technologies.

Kalkbrenner et al. [31] presented the assessment of their novel type-4 sleep monitor. The study was aimed at classifying sleep stages based on tracheal body sound and actigraphy. The tracheal body sound was used to extract cardiorespiratory signals which are commonly used for sleep assessment, while the IMU was used to extract movement features such as sleeping position and movement. The system was made up of a body sound microphone attached to the suprasternal notch (near the trachea) and the IMU and other peripherals (battery and Bluetooth gateway) were attached using an abdominal belt. A linear discriminant classifier was used for the sleep stage automation. Data were obtained from 53 subjects (33 males and 20 females) for validation purposes. Sleep/wake classification yielded 96.9% accuracy and 0.69 Cohen's Kappa, Wake/REM/NREM classification resulted in 76.3% accuracy and 0.42 Kappa, and Wake/REM/light sleep/deep sleep classification produced 56.5% accuracy and 0.36 Kappa.

The study by Lauteslager et al. [32] was aimed at assessing the capability of the radar-based Circadia Contactless Breathing Monitor (model C100) and proprietary Sleep Analysis Algorithm for sleep-stage classification. The system predicts bed occupancy, sleep stages, and derives standardized sleep metrics using its analysis algorithm and pulsed ultra-wideband radar. Sleep stage classification was carried out on the dataset obtained using the C100 device and PSG. For nine participants (six males and three females) in 17 nights, an epoch-by-epoch recall was 75.0%, 59.9%, 74.8%, and 57.1%, for deep sleep, light sleep, REM, and wake, respectively. The overall accuracy was 66.7%. A group from the University of Fribourg in Switzerland performed an independent validation and the recall was 70.7%, 52.5%, 83.0%, and 55.3% for deep sleep, light sleep, REM, and wake, respectively, with an overall accuracy of 62.7% using data obtained from 24 participants. A direct comparison with a Fitbit device and Philips Actiwatch showed that the C100 outperforms them in estimating TST, SOL, WASO, REM Sleep, Deep Sleep, and REM Latency.

The purpose of the study by Zhang et al. [33] was to exploit Ambient Radio Signals for recognizing sleep stages and assessing sleep quality. The study presented the model, design, and implementation of SMARS, a system that uses tiny changes in breathing patterns to measure the quality of sleep. The system was built on a single RF link and has a coverage of up to 10 m to monitor breathing. It was designed using off-the-shelf devices. The system consists of a Tx equipped with two antennas that by default transmits standard Wi-Fi packets at a rate of 30 Hz, and an Rx with three antennas that capture Channel State Information (CSI) of every packet it received from the Tx. It combines instantaneous breathing rate estimation and sleep monitoring. CSI is a statistical model on the motion that was developed to take into account both reflection and scattering multipath indoors. For fast estimation, a statistical approach that examines the autocorrelation function of CSI power response was adopted. SMARS was deployed in six homes and sleep data of 32 nights (about 234 h) were collected in total. Tx and Rx were placed on opposite sides of the bed during data collection. For comparison, PSG data of six participants (five males and one female) were collected to establish ground truth. Additionally, an open dataset on four state-of-the-art RF-based respiratory monitoring systems containing 160 h of overnight sleep data was used for validation. In terms of sleep stage recognition accuracy of SMARS compared to commercial products EMFIT and ResMed, SMARS achieved accuracies of



87%, 89%, and 87% for the wake, NREM, and REM detection, respectively. This was better than EMFIT with 77%, 75%, and 46%, and ResMed with 53%, 87%, and 79% accuracies. Additionally, SMARS has a wide coverage as it achieves a detection rate above 90% when the subject is 8 m away and 88.7% and 65% at 9 and 10 m, respectively. SMARS is a promising system for remote sleep monitoring. The system provided a good estimation of sleep stages compared with PSG based on the results. SMARS has served as a benchmark of comparison for other sleep monitoring devices such as Wi-Fi-Sleep by Yu et al. [15].

Inspired by recent advancements in Wi-Fi-based sensing, Yu et al. [15] presented a system to monitor and classify sleep. Wi-Fi-Sleep is based on Wi-Fi transceivers and a deep learning method. The system extracts accurate respiration and body movement and can classify sleep into four stages. The Channel State Information ratio was used to eliminate blind spots for improved detection. The effectiveness of the system was evaluated by experimenting with 12 subjects over 19 nights, a process in which it achieved an accuracy of 81.8% for four-stage sleep classification. The ground truth was obtained from PSG and the performance was compared with SMARS and RF-Sleep. The accuracy of the four-stage sleep classification for the other two devices is 79.8% and 69.4%, respectively.

#### 4. Discussion and Viewpoints

In the literature, it can be noted that there is an increasing interest in sleep monitoring (in particular, sleep cycles) using unobtrusive sensors. Due to the unsuitability of PSG for in-home monitoring, researchers have developed and are developing various unobtrusive systems as alternatives, leveraging on recent technological advancements. Generally, proposed sleep monitoring methods are based on one or a combination of the following: respiratory cycle, cardiac cycle, body movement [34]. We also observed that the majority of the proposed systems are limited to three-stage sleep classification [34]. Although the results from the abovementioned studies are encouraging in terms of accuracy, commercial devices cannot produce identical results to PSG. It makes sense because EEG-based systems are the most accurate for detecting all the stages of sleep [35].

That said, the ease and relative performance of actigraphy-based devices for sleep and sleep-cycle monitoring has given rise to numerous wearable devices and smartphone-based technologies. Actigraphy devices enable the user to wear dedicated sensors to help track vital signs and movements while sleeping. This review shows that the use of wearable devices for sleep-cycle monitoring is feasible but inaccurate compared to the gold standard PSG [30,36,37]. This is because even in healthy adults accelerometry has high sensitivity but low specificity for sleep detection. These devices often tend to underestimate or overestimate some key parameters such as TST, sleep efficiency, wake, or the transition between the sleep stages [30,36,37]. Patients with sleep disorders, or those who are chronically sleep-deprived, are more likely to suffer from fragmented sleep and reduced ability to understand their functional impairment. Therefore, wearing sleep trackers with incorrect readings could have adverse effects on these patients. This happens because most patients do not realize that the claims of these devices typically outweigh the science to support them as devices to measure and improve sleep. As a result, the importance of precise measurements cannot be overstated [36].

A recent study by Chinoy et al. [38] has shown that off-the-shelf sleep trackers (i.e., Fatigue Science Readiband, Fitbit Alta HR, EarlySense Live, ResMed S+, SleepScore Max) provided mixed results for sleep stage classification and the trackers tended to perform worse on nights with poorer/disrupted sleep. Similarly, Roomkham et al. [39] have come to the same conclusion that further studies are needed to assess the longer-term performance of sleep trackers, namely, the Apple Watch in natural conditions, and against PSG in clinical settings. Furthermore, Kholghi et al. [40] concluded that EMFIT QS failed to distinguish sleep stages against PSG and additional development is needed before using EMFIT QS in clinical settings. Moreover, studies have shown that although smartphone-based sensing systems are simpler and less expensive, they correlate poorly with the PSG [41].

Frankly, it is impractical to compare or generalize the accuracy across sleep trackers, specifically for under-mattress sleep trackers. This inconsistency occurs because the morphological characteristics of acquired BCG signals are device dependent. Besides, the signals can be different between and within subjects [37,42]. As a result, there is a need for a comprehensive and open dataset of BCG signals that will enable researchers to utilize them in their environments and improve the field into an accepted technique suitable for clinical studies [34]. To date, there is only one publicly available dataset of BCG signals; the purpose of the dataset was to assess the ability of the BCG to monitor changes in cardiovascular function [43].

Inventors have proposed, produced, and presented several methods (models and devices) for sleep monitoring by acquiring physiological data unobtrusively. However, the efficacy of a few systems was clinically validated. Experiment-wise, most of the studies are limited to a small sample of healthy individuals [39]. Thus, a broader scope of participants should be taken into consideration during future proposals and assessments of sleep-cycle tracking systems. This is because factors such as gender, age, profession, and social class affect the quality of sleep (Cappuccio et al. [44]).

Despite the above criticism, commercial sleep trackers can provide continuous and long-term monitoring of patients' sleep quality for days and weeks, which is impossible in hospitals. In other words, they can be used as predictive screening methods before performing the sleep studies [34]. For example, Sadek et al. [45] have shown the efficiency of an under-mattress sleep tracker for long-term monitoring of specific sleep parameters, namely, wake-up time, bedtime, and time in bed. These parameters were trended over time, and the authors were able to detect anomalies and notify corresponding caregivers.

Typically, under-mattress-based sensors can monitor the sleep quality of patients without interfering with their daily activities. However, this may not always be the case for wearable sensors considering vulnerable populations with behavioral symptoms. To explain, if the sensor is not waterproof, it has to be removed before showering. In addition, if the sensor has a short battery life, it needs to be removed frequently for charging. These situations will undoubtedly distract patients and similarly disrupt the data collection [46,47]. The choice between wearable and non-wearable sensors should be based on the medical conditions of each patient group. Hence, there will always be a trade-off between data continuity and patient comfort [46]. Following our discussion, we conclude the paper in the next section.

## 5. Conclusions

This review gives an overview of the current state and performance of sleep-cycle monitoring using contactless sensors. The review features the importance of sleep, a discussion of sleep monitoring and polysomnography, a review of existing works in sleep cycle monitoring, a discussion of the takes from the review, and highlights potential concepts that could be explored. With the rising interest in sleep monitoring generally and the clinical need for sleep cycle monitoring, there is an opportunity for researchers and commercial organizations to produce systems that will provide reliable and valid sleep information. Sleep monitoring is a very critical medical issue that could avert negative consequences on the life of individuals. It could potentially reduce the volume of fatigue-related work injuries, health issues, underperformance, road accidents, and aid health workers in managing sleep disorder patients. The performance and features of the systems examined in this review are encouraging. They could be set up for remote sleep-cycle monitoring and long-term studies, and they are easy to use. Unlike the gold standard-PSG, they are unobtrusive and contactless.

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## Appendix A

**Table A1.** The keywords and phrases used to retrieve the publications related to contactless monitoring of sleep cycles.

Keywords
<ul style="list-style-type: none"> <li>• Sleep;</li> <li>• Sleep cycle;</li> <li>• Sleep monitoring;</li> <li>• Sleep cycle monitoring;</li> <li>• Sleep monitoring system;</li> <li>• Sleep cycle monitoring using contactless sensors;</li> <li>• Sleep stage monitoring;</li> <li>• Automatic sleep stage classification;</li> <li>• Automatic sleep stage detection using contactless sensors;</li> <li>• Sleep stage monitoring based on heart rate;</li> <li>• Contactless sleep monitoring;</li> <li>• Sleep stage monitoring based on cardiac cycle;</li> <li>• Sleep stage monitoring based on the respiratory cycle;</li> <li>• Sleep stage monitoring based on physiological factors;</li> <li>• Polysomnography;</li> <li>• Ballistocardiography;</li> <li>• Non-contact sleep monitoring;</li> <li>• Sleep and wearable devices;</li> <li>• Bed sensor system;</li> <li>• Sleep-cycle monitoring based on physiological factors using contactless sensors.</li> </ul>

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