Review

Recent advances in wearable sensors and portable electronics for sleep monitoring

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SUMMARY

Despite the increasing awareness of the importance of sleep, the number of people suffering from insufficient sleep has increased every year. The gold-standard sleep assessment uses polysomnography (PSG) with various sensors to identify sleep patterns and disorders. However, due to the high cost of PSG and limited availability, many people with sleep disorders are left undiagnosed. Recent wearable sensors and electronics enable portable, continuous monitoring of sleep at home, overcoming the limitations of PSG. This report reviews the advances in wearable sensors, miniaturized electronics, and system packaging for home sleep monitoring. New devices available in the market and systems are collectively summarized based on their overall structure, form factor, materials, and sleep assessment method. It is expected that this review provides a comprehensive view of newly developed technologies and broad insights on wearable sensors and portable electronics toward advanced sleep monitoring as well as at-home sleep assessment.

INTRODUCTION

We spend almost one-third of our lifetime asleep. Sleep is an integral aspect of our life to sustain our daily activity, and the quality of sleep has a massive influence on our health, work performance, and well-being. Numerous research works have shown the association between the poor quality of sleep and many adverse effects on our health including, but not limited to, obesity, diabetes, heart diseases, hypertension, mood disorders, weakened immune system, and increased mortality risk (Buysse, 2014; Hublin et al., 2007; Patel et al., 2004; Sigurdson and Ayas, 2007). As an increasing number of people recognize sleep quality as a key component of a healthy lifestyle, research and industries related to sleep health have been actively growing. In 2019, the global sleep economy was $432 billion and was expected to grow up to $585 billion by 2024 with a compound annual growth rate (CAGR) of 6.3% (Casper, 2020). Especially when the COVID-19 outbreak has become a global pandemic, the importance of sleep is emphasized to support people's immunity and health (Gulia and Kumar, 2020; Huang and Zhao, 2020; Sher, 2020).

Despite this elevated awareness of sleep health, the number of people with insufficient sleep or sleep disorders has continuously increased. In 2015, it was reported that 18% of the United States population took less than 6 h of sleep per day. Insufficient sleep caused reduced labor productivity and increased mortality, leading to an economic loss of $411 billion, which is expected to grow up to $467 billion in 2030 (Hafner et al., 2016). Furthermore, in 2015, the American Association of Sleep Medicine (AASM) reported that obstructive sleep apnea (OSA), one of the most prevalent sleep disorders, afflicted 12% of the adult population in the United States. AASM also noted that around 80% of people with OSA were undiagnosed, resulting in an economic burden of $149.6 billion due to loss in productivity and an increase in the risk of costly comorbidities (Watson, 2016). Despite their prevalence, sleep disorders are easily dismissed because their symptoms are hard to notice while asleep.

The current gold standard in assessing sleep is polysomnography (PSG), which involves comprehensive measurement of physiological changes during sleep. Required sensors monitor brain activities, heart activities, eye movements, muscle activities, blood oxygen levels, breathing patterns, body movements, snoring, and other noises (Ibáñez et al., 2019). However, its complicated setup and high cost discourage people from regularly getting tested and demote the utility of PSG from accurate sleep monitoring. To measure all required data during sleep, trained technicians at the hospital

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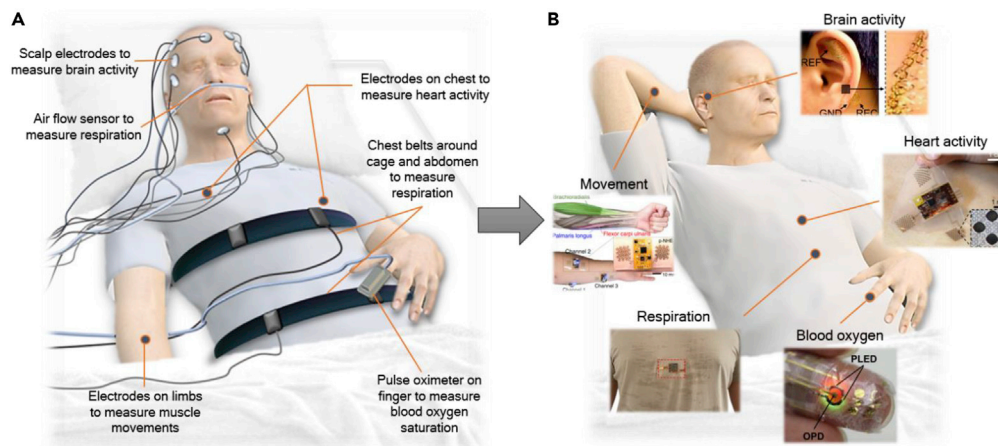
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Figure 1. Overview of the existing polysomnography (PSG) setup (left) and recently developed wearable devices (right) for sleep monitoring

(A) The conventional PSG setting that requires multiple wired sensors and transducers to measure sleep in a lab.
(B) A newly proposed PSG setup with recently developed wearable sensors and electronics systems to measure sleep at home. Low-profile wearable sensors can measure brain activity, heart activity, blood oxygen saturation, respiration, and movement. Brain activity image: reproduced with permission, from ref (Norton et al., 2015), Copyright 2015, National Academy of Sciences. Heart activity image: reproduced with permission, from ref (Kim et al., 2019), Copyright 2019, WILEY-VCH. Pulse wave image: reproduced with permission, from ref (Yokota et al., 2016), Copyright 2016, American Association for the Advancement of Science. Respiration image: reproduced with permission, from ref (Wei et al., 2021), Copyright 2021, American Chemistry Society. Movement image: reproduced with permission, from ref (Kwon et al., 2020), Copyright 2020, Springer Nature.

should place various sensors throughout the patient's body and set up convoluted wires and bulky electronics to transmit and store the data. Because the recordings must take place in a specialized laboratory unwelcome for natural sleep, many patients experience difficulties in falling asleep and do not show natural sleep behavior besides the complicated setup on their body. Recent progress in wearable device technology presents an alternative platform for home sleep monitoring to resolve the current challenges with PSG. Recently reported articles regarding sleep monitoring had summarized new systems in various aspects, such as the new systems' accuracy and sleep intervention level. However, their topics are limited to applying commercially available devices in the market (Guillodo et al., 2020; Ibáñez et al., 2019).

Here, this perspective summarizes the recent progress in wearable sensors and portable electronics that can enable comfortable and accurate sleep assessment even at home. Newly developed systems that are simply wearable and low-profile are collectively reviewed to envision possibilities of future home sleep monitoring trends. This report includes sections composed of summaries on devices with measurement of various signal types categorized by PSG's main physiological parameters. The recent development of the home sleep monitoring systems and their technologies are presented, and their overall structure, form factor, materials, and their method of sleep assessment are described. Finally, current challenges and future developments of wearable sleep monitoring systems are discussed.

RECENT PROGRESS OF WEARABLE SENSORS AND PORTABLE ELECTRONICS FOR SLEEP ASSESSMENT

This report's main contribution is to summarize recent outcomes in developing novel wearable sensors and portable electronics for sleep monitoring. Figure 1 shows an overview of PSG setup with the existing required devices (left) and recently developed wearable devices (right) for sleep assessment. There are multiple wearable sensors and specific locations to measure sleep-related signals, including brain activity, heart activity, blood data, respiration, and movement. Table 1 summarizes a list of recently developed wearable systems for sleep monitoring. Table 2 shows the summary of the advantages and disadvantages of wearable sleep devices that measure each of the five sleep-related signals and recommended design requirements for each device.

Table 1. Summary of recently developed wearable systems for sleep monitoring applications

Parameters	Data	Sensors	Sensor locations	References
Brain waves	EEG	Wet/dry electrode	Scalp	(Arnal et al., 2019)
			Forehead	(Arnal et al., 2019), (Levendowski et al., 2017), (Lin et al., 2017), (Shustak et al., 2019)
			Ear	(Alqurashi et al., 2018), (Sterr et al., 2018), (Mikkelsen et al., 2019)
Heart activity	ECG	Wet/dry electrode	Chest	(Klum et al., 2020), (Ilen et al., 2019), (Di Rienzo et al., 2018), (Yoon et al., 2018)
	ICG	Wet electrode	Chest	(Klum et al., 2020)
	PCG	Stethoscope	Chest	(Klum et al., 2020)
	SCG	Accelerometer	Chest	(Di Rienzo et al., 2018)
Pulse wave	PPG	LED & photodiode	Finger	(Liao et al., 2020), (Kinnunen et al., 2020)
			Nose	(Manoni et al., 2020)
			Forehead	(Arnal et al., 2019), (Levendowski et al., 2017)
	SpO2	LED & photodiode	Wrist	(Braun et al., 2020)
			Forehead	(Beppler et al., 2018)
			Ear	(Davies et al., 2020)
	IPG	Dry electrode	Wrist	(Schneider et al., 2018)
	Pulse pressure	Pressure sensor	Wrist	(Meng et al., 2020)
Respiration	Body movement	Strain gauge, accelerometer, magnetometer	Chest	(Klum et al., 2020), (Ding et al., 2018), (Ramírez et al., 2019), (Di Rienzo et al., 2018), (Milici et al., 2018)
			Head	(Arnal et al., 2019)
	Air flow	Humidity sensor	Nose	(Jin et al., 2017)
	Lung sound	Stethoscope	Chest	(Klum et al., 2020)
Movement	EMG	Dry electrode	Leg	(Jortberg et al., 2018)
	Actigraphy	Accelerometer, gyroscope, magnetometer	Wrist	(Liao et al., 2020), (Kwasnicki et al., 2018)
			Leg	(Bobovych et al., 2020)
			Chest	(Ilen et al., 2019), (Kwasnicki et al., 2018)
	Body position	Accelerometer, gyroscope, magnetometer	Wrist	(Kwasnicki et al., 2018)
			Chest	(Yun et al., 2020), (Kwasnicki et al., 2018)
			Nose	(Manoni et al., 2020)
Others	EDA	Dry electrode	Wrist	(Romine et al., 2019), (Kim et al., 2021)
			Finger	(Lam and Szypula, 2018)
	Tongue deformation	Ultrasonic transducer	Chin	(Weng et al., 2017)
	Body temperature	Thermometer	Chest, wrist	(Di Rienzo et al., 2018), (Liao et al., 2020)
	Snoring sound	Microphone	Forehead	(Levendowski et al., 2017)

Wearable devices for monitoring brain signals

The brain plays a central role in controlling various biological and physiological processes and changes in our body and within the brain during a night of sleep (Hobson, 2005). Changes in brain activities are often the most direct indicator of five different sleep stages (W, N1, N2, N3, and REM) and any abnormalities happening in sleep disorders (Berry et al., 2017). Thus, studies and assessment of sleep begin from monitoring brain activity changes by measuring brain waves with an electroencephalogram (EEG) during sleep. Therefore, the measurement of EEG is an indispensable component of any sleep monitoring system that aims to analyze sleep in detail. Standard PSG, for example, dedicates the greatest number of electrodes for the measurement of EEG on the scalp. The biggest design challenge of sleep monitoring devices that can be used outside of hospitals is making electrodes that can measure EEG from the scalp, mostly covered by hairs (Arai et al., 2016). In standard PSG, conductive gels are widely used to penetrate through the hairs and make an electrical path between the scalp

Table 2. Advantages and disadvantages of wearable sleep devices that measure each of the five popular signal types and their recommended design requirements for successful sleep measurement.

Signal type	Advantages	Disadvantages	Design requirement
EEG	• Highest accuracy in specific sleep stage analysis and detection of various sleep disorders.	• The device should be placed on the head; it may bother the user's sleep. • Requires direct contact between sensor and skin. • Signal quality depends on skin condition.	• Reasonable inter-electrode distance to ensure good signal strength. • High-resolution DAQ system to measure brain waves. • Combination with EOG and chin EMG for higher accuracy • Novel material for the electrode to ensure reliable contact with skin. • Minimized sleep disturbance with the novel form factor.
ECG	• Gold standard in cardiac monitoring and cardiac disorder diagnosis.	• Sensor location is usually restricted to chest to obtain high SNR. • Requires direct contact between sensor and skin. • Signal quality depends on skin condition.	• Reasonable inter-electrode distance to ensure good signal strength. • Novel material for electrode to ensure reliable contact with skin. • Minimized sleep disturbance with novel form factor. • Placement of sensor on chest to ensure high signal quality with minimized motion artifact.
PPG/SpO2	• Smaller, cheaper replacement for ECG. • Can be measured from multiple different body locations (wrist, nose, etc.). • SpO2 is effective in diagnosis of apnea.	• Although it can be measured on various body parts, just few locations (finger, earlobe, etc.) provide reliable signal quality, especially for SpO2. • Requires direct contact between sensor and skin.	• Delicate control of number, configuration, wavelength, and brightness of LED and photodiode. • Choice of measurement location to maximize signal strength. • Wearable platform that can apply moderate pressure on skin (e.g., wristband).
Respiration (chest expansion)	• Most effective in diagnosis of sleep apnea events characterized by frequent stop in breathing.	• Provides little information for sleep analysis besides apnea events.	• Novel sensor material to maximize sensitivity (e.g., TENG). • Minimized sleep disturbance with novel form factor.
Actigraphy (body movement)	• Small sensor size. • Does not require direct contact between sensor and skin. • Comfortably worn in a wristband-type device.	• Despite reasonable accuracy in wake/sleep detection, specific sleep staging suffers lower accuracy.	• Combination with PPG and ambient light sensor to improve accuracy in sleep/wake detection.

and electrodes fixed in location by hair caps. However, the use of conductive gel and setting up electrodes with a hair cap is challenging for individuals and time consuming and bothersome for setting and cleaning up. Thus, many of the new systems try to use the forehead as an alternative location of EEG measurement due to its physical proximity to the brain and presence of smooth and relatively flat skin surface where either wet or dry electrodes can form a reliable contact (Myllymaa et al., 2016). For example, Advanced Brain Monitoring (California, United States) introduced its home sleep monitoring system named Sleep Profiler, which provides wireless sleep monitoring in a headband platform equipped with three frontopolar EEG electrodes on the forehead (Levendowski et al., 2017). This device is also equipped with a photoplethysmography (PPG) sensor, microphone, and a triaxial accelerometer to simultaneously monitor the pulse rate, snoring, and body movement. Along with the other data, the embedded software mainly analyzes the power spectrum of brain waves to detect specific events, such as sleep spindle and K-complex, and automatically classify the stages of sleep. The result of automated five-class sleep staging shows Cohen's kappa coefficient of 0.67 on average when compared with stages scored by five other sleep technologists over 33,635 epochs, when the average kappa score among the five sleep technologists was 0.70. Sleep profiler also measures various parameters and events of sleep, including sleep time, sleep latency, wake after sleep onset (WASO), etc. and compares their night-to-night variability.

Despite the barrier of hair, some new systems and studies have made breakthroughs to make electrodes with novel materials and structure to enable reliable and convenient EEG measurement on the scalp. Figure 2A shows a commercial device, Dreem Headband, that measures seven EEG derivations from three dry electrodes on the forehead and at the back of the head, two dry electrodes that are made of soft, flexible silicone protrusions to make contact with the scalp by penetrating through the hairs (Arnal et al., 2019). This wireless headband system also includes a PPG sensor to measure heart rate (HR), and a 3-axis accelerometer to measure movements, position, and respiration rate. This device was compared with PSG with 25 subjects over a single night sleep study and showed their high correlation of measured brain waves, HR, respiration rate, and respiration rate variability. Furthermore, their deep learning algorithm used for automated sleep staging was trained by a total of 423 datasets that are previously measured and showed Cohen's kappa coefficient of 0.748 on average with the five other scorers when the average kappa score among the five scorers was 0.798. The Dreem Headband provides various parameters related to sleep quality, such as total sleep time (TST), sleep onset latency (SOL), and WASO. More recently, other body parts other than the forehead have been tested to measure EEG with less obtrusion and interference with natural sleep behavior, and the ear is the most popular measurement location among them. Figure 2B shows an in-ear-type EEG measurement platform with two fabric-based EEG electrodes integrated with a memory-foam substrate (Alqurashi et al., 2018). The author explains that memory foam's unique mechanical property provides a comfortable fit to the user's ear, makes reliable skin-electrode contact, and effectively reduces signal artifacts from pulsatile ear canal movements due to blood vessel pulsation. The comparison study with EEG measured with commercial PSG over 21 subjects shows its capability to detect slow-wave sleep (SWS), measuring sleep latency, and automated five-stage sleep scoring. Automated scoring with in-ear EEG results in Cohen's kappa coefficient of 0.61 compared with the manual scoring and that of 0.79 with scalp EEG.

Another example of a new system with EEG measurement around the ear is shown in Figure 2C. This EEG measurement platform, "cEEGrid," is a flexible, thin adhesive strip with ten embedded electrodes with a structure that fits and attaches behind the ear (Sterr et al., 2018). The author emphasizes the convenience of the cEEGrid by showing that the user could complete the measurement setup alone within 20 min. The compared PSG setup took 45 min with the help of one well-trained sleep technician. To validate its performance, the data measured with cEEGrid and PSG setup were manually scored by trained scorers, and the average Cohen's kappa coefficient between scores from the two systems was 0.42. Lastly, Figure 2D shows another type of ear-mounted EEG measurement system with a total of 12 dry electrodes mounted on the two earplugs (Mikkelsen et al., 2019). This system was tested for 80 sleep measurements with 20 subjects simultaneously with a PSG setup to assess the system's convenience and performance. High convenience and comfort level was shown, as 19 of the 20 subjects reported that the system had little or no adverse effect on their sleep. They were generally able to wear the system on their ear without supervision. Moreover, a machine learning approach was adopted and trained with the sleep EEG data measured with the system to develop an automated scoring algorithm that showed Cohen's kappa value of 0.81 in five-stage sleep scoring compared with the manual scoring done with data measured with PSG setup.

Wearable heart-activity monitors during sleep

Other than brain activity, one of the most prominent physiological changes during sleep is the modulation of autonomic nerve balance, where our body shifts between sympathetic and parasympathetic dominance throughout sleep (Shinar et al., 2006). Blood pressure (BP) and HR decline as the sleep stage goes from awake to the N3 and then rapidly increases during REM up to a similar level as awake. Heart rate variability (HRV) and the ratio of its low frequency (LF) and high frequency (HF) power are the other parameters that differentiate different sleep stages (Stein and Pu, 2012). Among the multiple measuring cardiac activity methods, electrocardiogram (ECG) has been accepted as the gold standard. ECG is usually measured on the chest, and recently developed portable ECG devices have successfully minimized the size and maximized user convenience. With a less obtrusive measurement setup than EEG, ECG can provide useful information about the sleep and detect cardiac abnormalities associated with sleep disorders. Recently developed portable, convenient ECG measurement systems mostly adopt a single-lead system to achieve the compact size while measuring high-quality ECG signals. One example is T-REX from Taewoong Medical (Gyeonggido, South Korea) (Yoon et al., 2018). This wireless patch-type device comprises a fabric-based thin-flexible adhesive patch integrated with three electrodes and equipped with a 3-axis accelerometer. With the measured ECG and acceleration signal, HR, respiration rates, and body movement degree are estimated. The extracted parameters are then used for the wakefulness detection algorithm to
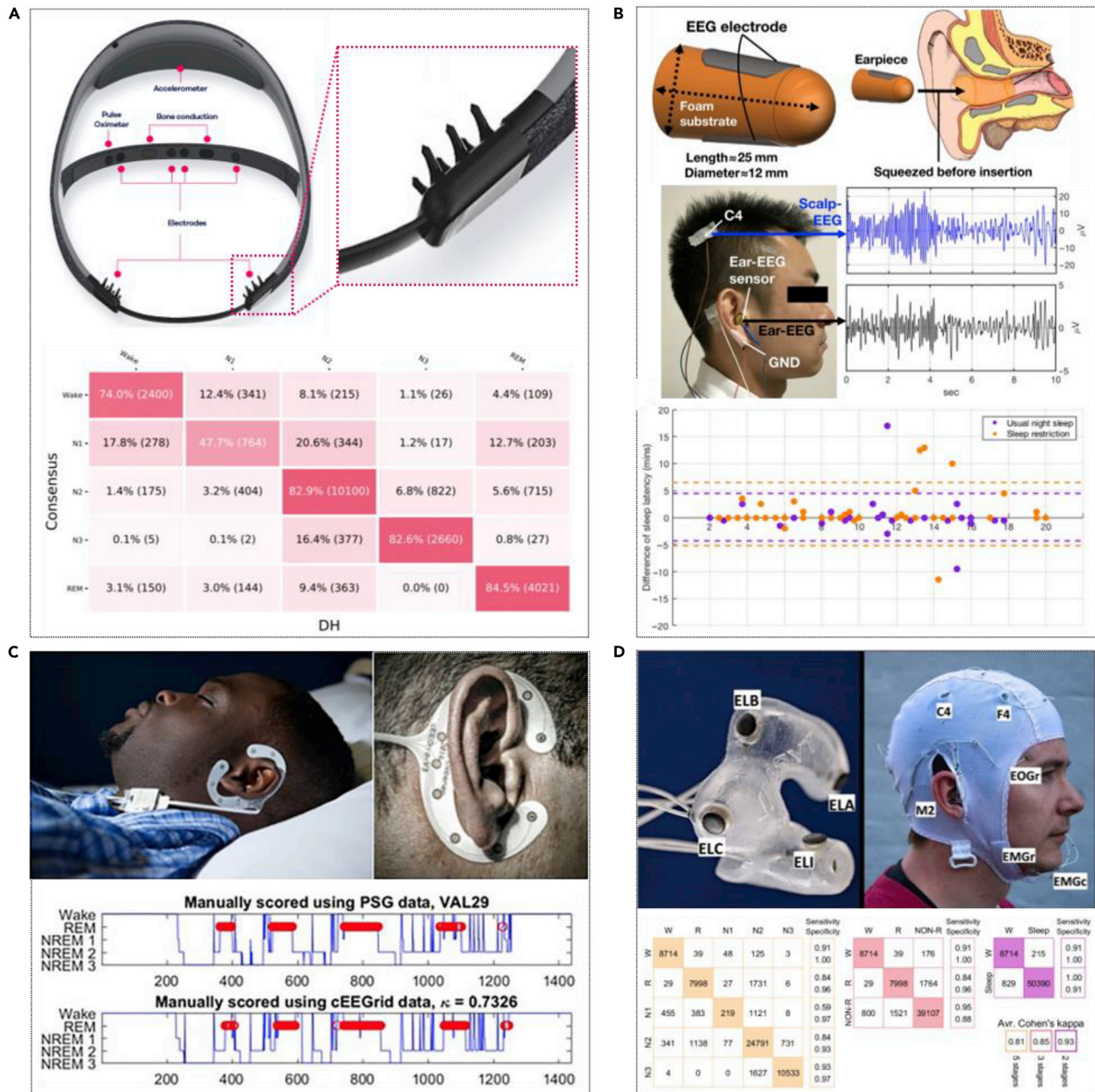
Figure 2. Examples of brain-signal monitoring wearable devices for sleep analysis

(A) Headband-integrated wearable electronics, including dry electrodes, silicone protrusion electrodes, accelerometer, and PPG sensor for measuring EEG, heart rate, and respiration rate during sleep. Confusion matrix showing an accuracy of automated sleep scoring algorithm. Reproduced with permission, from ref (Arnal et al., 2019), Copyright 2019, bioRxiv.

(B) In-ear memory foam system with conductive fabric-based EEG electrodes. Plots showing comparable signal quality to scalp EEG and sleep latency detection accuracy. Reproduced with permission, from ref (Alqurashi et al., 2018), Copyright 2018, Dovepress.

(C) Adhesive patch-type EEG system that attaches behind the ear. Hypnogram data compare the manually scored sleep stages from PSG and the patch system. Reproduced with permission, from ref (Sterr et al., 2018), Copyright 2018, Frontiers in Human Neuroscience.

(D) In-ear-type EEG recording system with integrated dry electrodes. Confusion matrices showing automated scoring results with the proposed system and its agreement with stages from PSG. Reproduced with permission, from ref (Mikkelsen et al., 2019), Copyright 2019, Springer Nature.
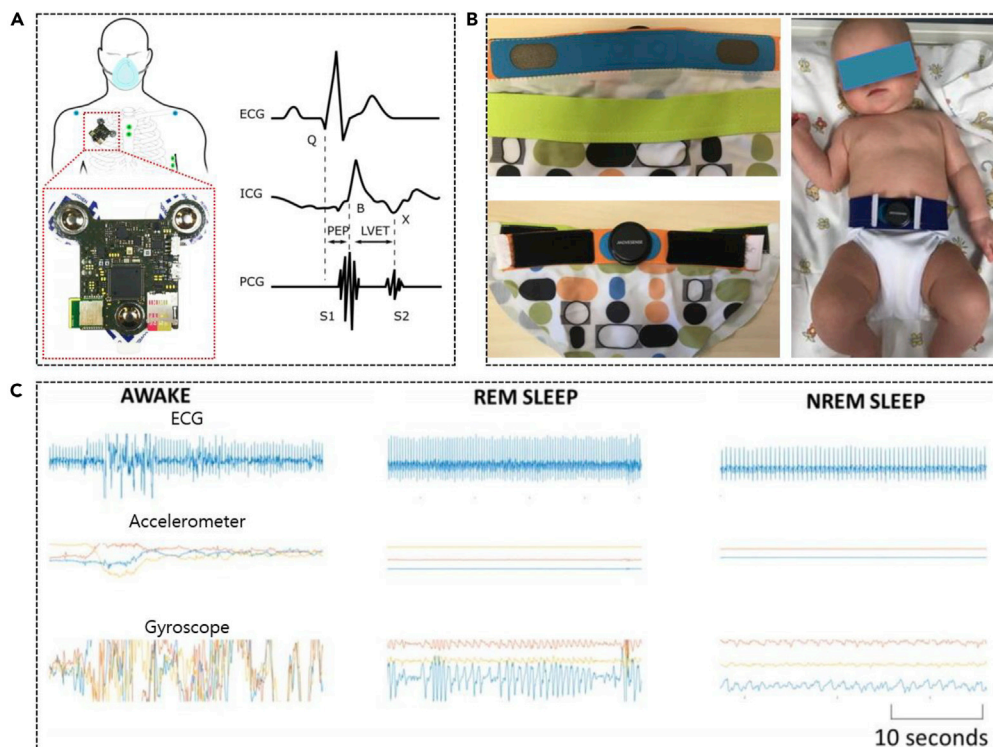
Figure 3. Examples of recent wearable heart-activity monitors used for sleep analysis

(A) Integrated, portable chest patch device for cardiac function (ECG, ICG, and PCG) monitoring with wet electrodes and a digital stethoscope. Reproduced with permission, from ref (Klum et al., 2020), Copyright 2020, MDPI.

(B) A baby pull-up pant, incorporating conductive fabric-based electrodes, accelerometer, and gyroscope to measure ECG and movements.

(C) Representative ECG and movement data measured from the wearable device in (B) at awake, REM, and NREM sleep stages. Reproduced with permission, from ref (Ilen et al., 2019), Copyright 2019, Universiteit Gent.

detect if the user is either awake or asleep with a machine learning approach, which showed an average Cohen's kappa of 0.60 for the comparison study with PSG with 30 subjects. The author expects that the algorithm can be further developed to work with REM and SWS detection with the same extracted parameters.

Figure 3A shows another example of patch-type device that measures ECG from the chest but with the added number of sensors and enhanced functionality (Klum et al., 2020). This wireless device also adopts single-lead ECG with three standard Ag-AgCl electrodes, used for impedance cardiography (ICG). This device's unique feature is that it has an integrated stethoscope that is used for further cardiac activity monitoring by phonocardiogram (PCG) and tracking of respiration by measuring the lung sound. These parameters are then collectively utilized to estimate HR and HRV and more detailed ECG activity, including a pre-ejection period (PEP) and left ventricular ejection time (LVET) with high accuracy on their developed detection algorithm. With this unobtrusive measurement of cardiac activity and respiration, the author expects its well-suited application on home sleep testing. To make the ECG measurement system less bothering, fabric-based sensors and dry electrodes are often integrated with the clothing and applied on sleep monitoring. Figure 3B shows pull-up-pants-type wireless device called Movesense, which has two integrated fabric ECG electrodes designed for sleep monitoring of infants who are more susceptible to the obtrusive method (Ilen et al., 2019). This device is designed to be worn over the diaper, and the two textile ECG electrodes integrated on the waistband contact the infant's abdomen. The device also has 3-axis motion sensors composed of an accelerometer, gyroscope, and magnetometer. The measured overnight sleep data showed a consistent signal quality that is clear enough to differentiate rapid eye movement (REM), non-REM (NREM), and awake stages (Figure 3C). Another example of the smart garment device is MagIC-Space developed by Rienzo et al., a sensory vest designed to wirelessly measure cardiac mechanical performance and vital signs of human during sleep microgravity environment such

as space station (Di Rienzo et al., 2018). MagIC-Space is integrated with two textile ECG electrodes on the chest and a textile plethysmograph band that wraps around the chest on top of the ECG electrodes for reliable electrode contact and respiration measurement. It also has two accelerometers placed on the sternum to measure seismocardiogram (SCG) for further cardiac health monitoring. This system could be tested and successfully measured vital signs for 42 h of sleep at the International Space Station (ISS). The signal quality was good enough that 96.5% of the heartbeat signals could be used to extract cardiac activity information such as PEP, LVET, isovolumic relation time (IRT), and isovolumic contraction time (ICT).

Wearable sensors and electronics for measuring pulse during sleep

Although ECG is treated as the gold standard for cardiac monitoring, measurement of pulse wave by PPG is widely accepted as a low-cost, simple, and portable alternative for HR and HRV measurement (Lin et al., 2014). PPG has been more popular than ECG for mobile devices due to its smaller size and easier structure and use. ECG requires multiple electrodes and is usually restricted to the chest to make a reliable, continuous measurement within a portable, wireless platform. Although recent smart wristband-type devices support ECG measurement on the wrist, continuous monitoring is not possible because it requires the finger from the other hand contact on the device (Isakadze and Martin, 2019). Recent research has explored alternative locations, such as the left arm, for continuous ECG measurement with a portable device form factor, but their signal quality is not fully validated yet (Escalona et al., 2017). In contrast, PPG needs just a single unit of LED and photodiode and can be measured on various body locations, making it easy to integrate into various existing wearable device form factors, especially a wristband. Standard PPG measurement is made with a clip-type sensor that applies constant pressure on a fingertip at which the measured PPG shows higher signal strength than the other explored alternative locations such as earlobe and wrist (Hartmann et al., 2019). To take advantage of high PPG signal quality from the finger and to make an unobtrusive PPG measurement method, the Oura ring (Oura Health, Oulu, Finland) provides comfortable and continuous PPG measurement in a finger ring structure (Kinnunen et al., 2020). This wireless finger ring PPG device was tested with 60 subjects compared with ECG to measure HR and HRV during sleep. The result showed a very high correlation in their measurements (r^2 = 0.972 and 0.943, respectively). The PPG measured with the Oura ring on subjects with arrhythmia, which is closely related to OSA, showed abnormal PPG waveforms, indicating its potential application in detecting an arrhythmia.

Figure 4A shows a nose-mounted wireless device, called MORFEA, with two PPG measurement units and one 3-axis accelerometer designed to detect sleep apnea (Manoni et al., 2020). By analyzing the PPG and accelerometer waveforms transformed by the nostril movement affected by sleep apnea, the device could detect the timing and type of apnea event (Figure 4B). MORFEA could also identify five different body positions during sleep with different offset values generated in accelerometer data (Figure 4C). By using PPG signals from two LEDs with wavelengths (usually red and IR), pulse oximetry can estimate the blood oxygen saturation (SpO_2). This is widely used in PSG and other health monitoring as one of the direct sleep apnea indicators. Like the PPG, the standard pulse oximetry is done on the fingertip. But, recent developments of the sleep monitoring system with pulse oximetry could measure signals on various other parts of the body. The most recent and well-known example of this is the smartwatches, such as Apple Watch 6 from Apple (California, United States) and Galaxy Watch 3 from Samsung (Seoul, South Korea). They are capable of measuring blood oxygen saturation throughout the day and night. Braun et al. have developed their own wireless, wrist-worn pulse oximeter, called PulseWatch, and validated its accuracy (Braun et al., 2020). PulseWatch is composed of green, red, and IR LEDs with a photodiode integrated on a wristband. It was tested on 54 subjects simultaneously with a standard finger clip pulse oximeter. It showed a root-mean-square error (A_{RMS}) of 3.4%, which complies with the FDA guidance requirements on reflectance-type pulse oximeter of $A_{RMS} < 3.5$.

Figure 4D shows another novel system that measures pulse oximetry in the ear canal (Davies et al., 2020). This device is composed of a pulse oximeter integrated with an in-ear-type structure. In-ear pulse oximetry's unique feature is that the change in blood oxygen saturation is detected 12.4 s earlier on average than the finger pulse oximetry (Figure 4E). The accuracy of the in-ear pulse oximetry compared with the standard finger clip pulse oximeter over 14 subjects across 60 s is validated with A_{RMS} of 1.47% (Figure 4F). The forehead is another body location for pulse oximetry that is tested and validated. Beppler et al. introduced an adhesive-bandage-type wireless device composed of LEDs and photodiodes, which attaches on the forehead to measure blood oxygen saturation (Beppler et al., 2018). The device tested on OSA patients could
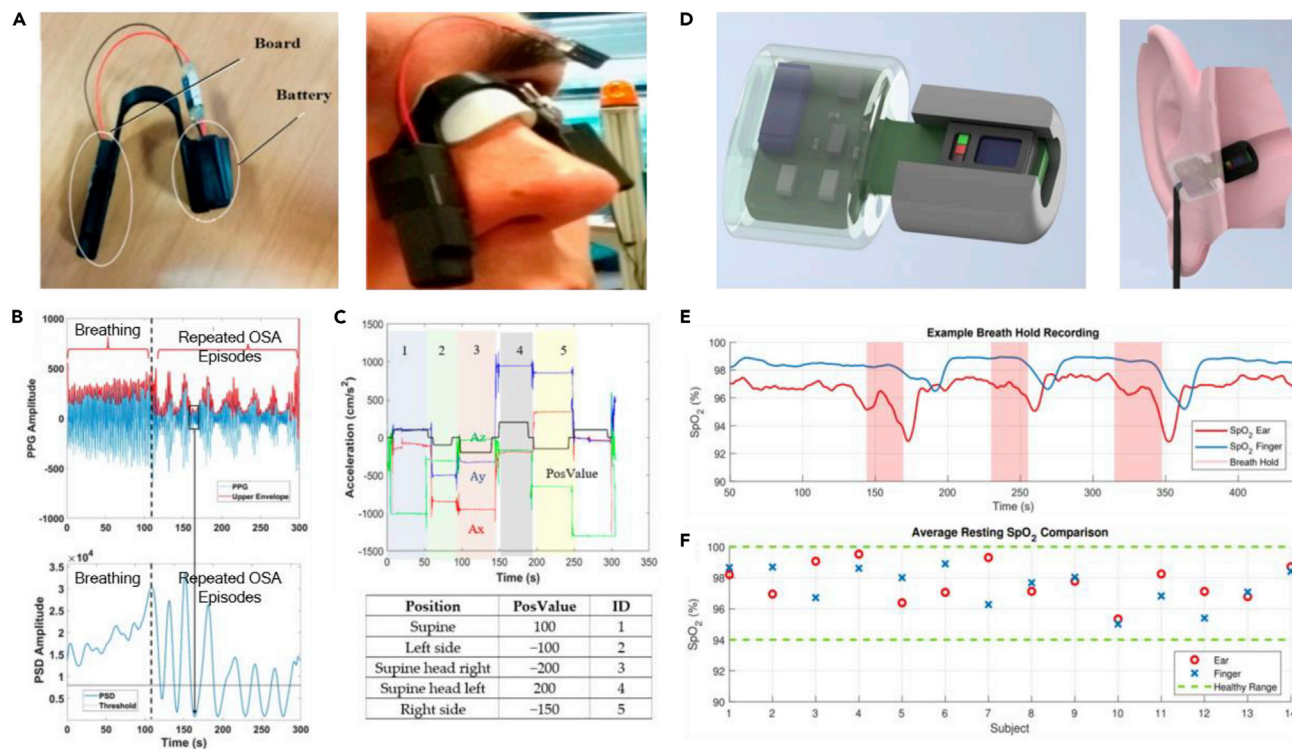
Figure 4. Summary of pulse-wave-based wearable sensors and electronics for sleep monitoring

(A) Nose-mountable device with integrated PPG sensor and accelerometer to detect apnea events during sleep while classifying five different sleep positions.

(B) Plots showing characteristics of PPG signals during normal breathing and apnea events.

(C) Graph (top) and table (bottom) showing sleep position profiles and their signal characteristics, measured by an accelerometer. Reproduced with permission, from ref (Manoni et al., 2020), Copyright 2020, MDPI.

(D) In-ear wearable pulse oximeter that measures blood oxygen saturation (SpO2).

(E) Plot showing SpO2 data from the in-ear device, compared with a standard finger-worn pulse oximeter.

(F) Plot summarizing resting SpO2 data from both devices with multiple subjects to validate the device accuracy. Reproduced with permission, from ref (Davies et al., 2020), Copyright 2020, MDPI.

capture repeated drops in blood oxygen saturation. Other than the optical method of pulse wave measurement, other modes of measurements are observed and tested for pulse wave measurement during sleep. A wristband-type impedance plethysmography (IPG) measurement device is introduced and validated (Schneider et al., 2018). The device comprises four silver-based dry electrodes and wireless circuitry that measure the skin's impedance, which keeps periodic change due to the blood pulses. A comparison study with ECG showed its high accuracy in measuring HR and HRV. Another example is a textile-based triboelectric strain sensor in a wristband structure for pulse wave measurement (Meng et al., 2020). The pulse on the wrist creates a physical deformation in the triboelectric textile sensor that induces electrical signals. This textile-based pulse wave sensor was tested for pulse measurement during sleep and showed clear pulse waveforms, and abnormal waveforms were observed when tested on the OSA patient, indicating the apnea events.

Wearable sensor systems for monitoring respiration during sleep

Measurement of respiration pattern is another widely used sleep monitoring method next to EEG. Its foremost objective is to detect any abnormal respiratory behavior caused by sleep apnea and hypopnea and evaluate their severity. Apnea is a breathing disorder that happens during sleep, which is characterized by repeated pauses in breath. As discussed in the introduction, due to the increasing prevalence and side effects of sleep apnea, breathing and pulse oximetry monitoring becomes more important for detecting and diagnosing apnea (Punjabi, 2008). One of the main methods in monitoring respiration during sleep is measuring nasal airflow by putting a thermally sensitive sensor near the nostrils. A previous work (Jin et al., 2017) proposed a novel, less-obtrusive system for nasal airflow monitoring and OSA detection during

sleep based on the surface acoustic wave (SAW). The SAW sensor is composed of 3-μm thick ZnO piezo-electric thin film deposited on 100-μm thick polyimide (PI) film. The thin, flexible sensor is placed around the nostrils and monitors respiration using its sensitivity to humidity change. This system's unique characteristic is that it is a passive wireless system that does not require a battery or direct power input to the system. The respiration signal is acquired by an external reader that sends an interrogation signal with a fixed operation frequency to the sensor and reads the reflected response signal with a frequency that changes with the humidity.

Other than the nasal airflow sensor, respiratory inductance plethysmograph (RIP) belts are also commonly used to monitor respiration during sleep by measuring the chest and abdomen's physical expansion. Figure 5A shows a new type of sleep monitoring chest belt made of triboelectric nanogenerator (TENG) (Ding et al., 2018). TENG is relatively a new technology, and its application has been a popular research topic due to its advantages, including flexibility, fast response, high sensitivity, and excellent durability. In this example, carbon nanotube (CNT)-doped porous PDMS is used for further improved sensitivity. The sleep monitoring belt made of CNT-doped porous PDMS could measure the subject's inhale and exhale motion, and its high sensitivity also enables detection of heart pumping (Figure 5B). Figure 5C shows another example of a chest-worn respiration monitoring system with a further minimized form factor. This stretchable tattoo-like strain sensor comprises the composite of single-layer graphene, ultrathin granular palladium, and conductive polymer based on PEDOT:PSS (Ramírez et al., 2019). This composite structure provides highly enhanced piezoresistive sensitivity and mechanical stability (Figure 5D). It is reported that this structure can detect strains as low as 0.001% with stretchability up to 86%. This composite sensor is encapsulated with a soft PDMS substrate to be used on the skin. The sensor, attached to a subject's chest, makes a physical deformation caused by inhaling and exhaling, and individual heartbeats could also be detected (Figure 5E). Besides the strain-based sensing method, a simple, small-size, low-power monitoring system on the chest could be developed using the motion sensor. Milici et al. built a battery-powered, wireless chest belt with an embedded magnetometer to measure the change in its orientation caused by breathing motion (Milici et al., 2018). An algorithm for respiration rate calculation is developed with the data measured with the magnetometer chest belt. A comparison study with a nasal airflow sensor showed a high correlation coefficient over 0.85. The system could also detect apnea when a pause in breathing is observed.

Wearable portable electronics for monitoring body movements

In standard PSG, an electromyogram (EMG) signal on limbs is measured to monitor limb movements and muscle activation. These measurements from limbs are used to identify when the patients are awake and to detect various sleep disorders, including periodic limb movements in sleep (PLMS), alternating leg muscle activation (ALMA), and hypnagogic foot tremor (HFT). To achieve the monitoring of limb movements at home, BioStampRC from MC10 (Massachusetts, United States) provides a wireless, flexible, adhesive patch-type device that is capable of measuring various electrophysiological signals, including leg EMG (Figure 6A) (Jortberg et al., 2018). BioStampRC shows comparable leg EMG signal quality to the PSG leg EMG measurement and can detect events of PLMS (Figure 6B). When attached to the chest, this device can measure ECG and respiration rate with its embedded accelerometer during sleep. Actigraphy (ACT) is widely accepted as an at-home sleep monitoring method that measures body movement with a wearable accelerometer, usually in a wristband form factor (Morgenthaler et al., 2007) (Sadeh, 2011). Despite its inherent limitation in the analysis of sleep quality or direct monitoring of sleep disorders, ACT is popular due to its easy, low-cost, and unobtrusive application in evaluating sleep-wake patterns. Figure 6C shows an example of a wristband-type device that utilizes accelerometer-based ACT. The accelerometer also incorporates an ambient light sensor, temperature sensor, sound sensor, and finger-PPG sensor (Liao et al., 2020). To evaluate the sleep-wake pattern, the device mainly looks at the movement and strength of ambient light. Its performance is compared with an FDA-approved wristband-type ACT device, Actiwatch 2 from Phillips (Amsterdam, Netherland), which also uses the same evaluation parameters (Figure 6D). Comparison test over seven nights of sleep showed an average difference of 1.36% in the evaluation of total sleep duration, showing the device's comparable performance.

Another example from Kwasnicki et al. utilizes three motion sensors placed on the chest and both wrists to detect various sleep postures and evaluate sleep quality (Kwasnicki et al., 2018). Each motion sensor is composed of a 3-axis accelerometer, gyroscope, and magnetometer, and their data are wirelessly
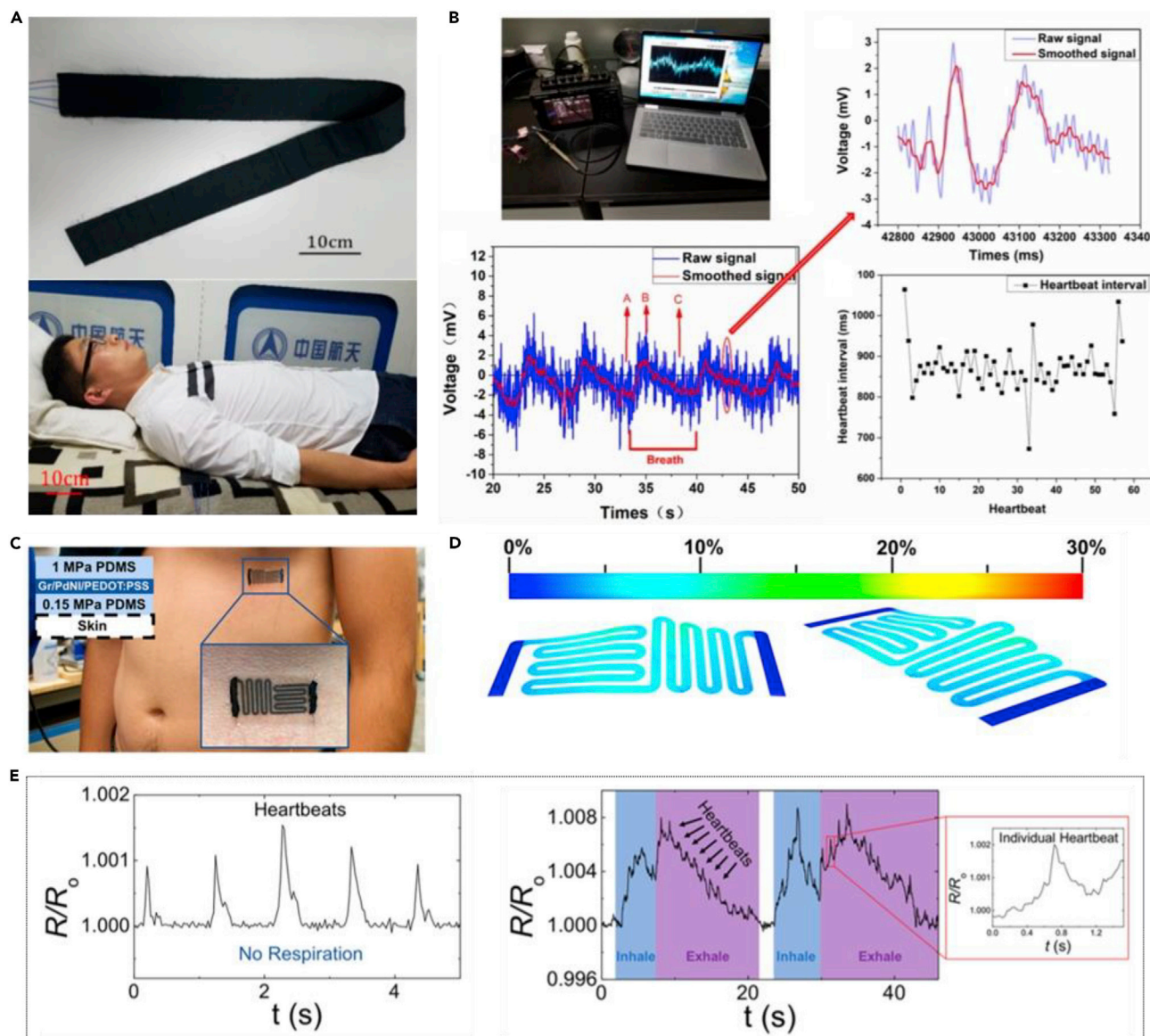
Figure 5. Summary of wearable sensor systems for monitoring respiration during sleep

(A) TENG-based chest belt, made of CNT-doped porous PDMS, to monitor respiration during sleep.

(B) Plots showing measured breath and heartbeat signals. Reproduced with permission, from ref (Ding et al., 2018), Copyright 2018, MDPI.

(C) Tattoo-like piezoresistive strain sensor, made of a composite of graphene, palladium, and PEDOT:PSS, for enhanced sensitivity and mechanical stability.

(D) Finite element analysis results of the strain sensor in (C) under deformation from respiration and heartbeat, showing its mechanical reliability.

(E) Two plots showing heartbeat and respiration signals measured by the wearable strain sensor. Reproduced with permission, from ref (Ramírez et al., 2019), Copyright 2019, American Chemical Society.

measured. Classification of eight different sleep postures was tested with this device over ten subjects, which showed an accuracy of 92.5%. Furthermore, based on the magnitude of body movement measured from the three sensors, the device could differentiate and measure the duration of awake, NREM, and REM sleep stages. Sleep stage and duration measurement test over five subjects with simulated study showed 97.3% accuracy. Figure 6E shows a fully portable, low-power, wireless sleep position sensor based on an accelerometer for infants (Yun et al., 2020). By utilizing novel power-saving circuitry and powering algorithm, the power consumption could be reduced below 1 mW. With this low power requirement, a flexible paper battery could power the system to make the system thin and flexible. This device is worn on the back of the baby and detects when the baby's sleep position changes to a prone position that can disturb the
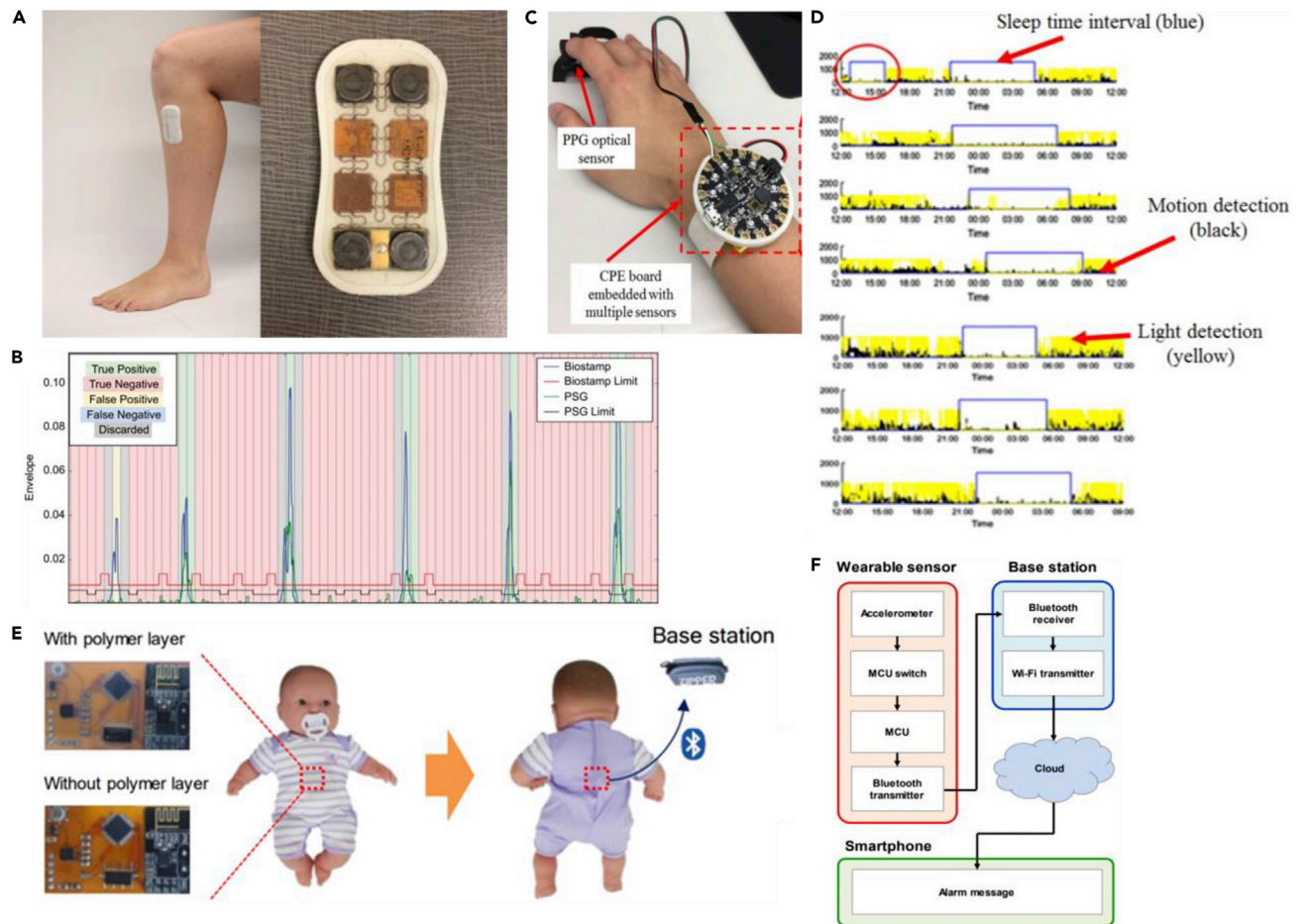
Figure 6. Examples of wearable portable electronics for monitoring body movements

(A) Flexible adhesive patch with integrated electrodes to measure leg-EMG during sleep.

(B) Comparison of PLMS event detection between the patch in (A) and the conventional PSG for performance validation. Reproduced with permission, from ref (Jortberg et al., 2018), Copyright 2018, Dovepress.

(C) Wrist wearable electronics incorporating accelerometer, ambient light sensor, and finger PPG sensor to monitor the user's activity, HR, and strength of ambient light for sleep-wake pattern identification.

(D) Plots showing measured activity, ambient light level, and detected sleep interval throughout the seven days of use. Reproduced with permission, from ref (Liao et al., 2020), Copyright 2020, MDPI.

(E) Low-power, flexible wearable device with an accelerometer to monitor infants' sleep posture and alert caregivers when a prone position is detected.

(F) Schematic diagram showing the workflow of the proposed device from the detection of sleep posture and sending an alert message to the caregivers. Reproduced with permission, from ref (Yun et al., 2020), Copyright 2020, MDPI.

baby's breathing and lead to a tragic situation. When the device detects the prone position, it sends a signal to the base station near it, which then immediately sends an alarm message to the caregiver to reposition the baby (Figure 6F).

Wearable systems for monitoring additional sleep-related signals

Recent advancements in wearable sensors and devices have also observed the potential application of various other types of physiological signals in sleep monitoring. Measurement of electrodermal activity (EDA), a measure of skin's electrical properties, has been a popular topic as a new dimension to take a look at the sleep. Lam et al. developed a flexible and wireless integrated EDA device that can be worn on fingers during our daily life, including sleep (Lam and Szypula, 2018). The EDA data measured with this device could show a clear difference in skin conductance level between when the subject was awake and asleep. The measurement could also observe few EDA storms every few hours during sleep, especially when the subject woke up from a bad dream. Empatica E4 is a commercially available wireless, wristband-

type device with multiple sensing functionality and EDA measurement from the wrist. EDA measured with Empatica E4 during sleep showed similar observations. Several EDA features, such as average size and standard deviation of EDA storms, could be associated with the sleep efficiency and sleep quality reported from the subject (Romine et al., 2019).

Kim et al. presented a fully integrated, wireless soft electronic system designed to measure EDA from the wrist. The dry electrodes used in this epidermal device are a composite of very thin, closed-mesh-patterned PI and graphene printed based on aerosol jet printing technology (Kim et al., 2021). The electronic circuit comprises thin, close-mesh-patterned copper traces fabricated with thin-film metal and polymer processing with photolithography. The key components are all integrated on a soft silicone elastomer substrate and feature superior flexibility and stretchability. This device measures EDA on the wrist with partial PSG setup while showing a varying amount of EDA activity during awake and four different sleep stages (N1, N2, N3, and R). This work shows the device's potential application in sleep monitoring and stage classification. This paper shows an association between the EDA activity and different sleep stages through statistical analysis using ANOVA with an F value of 6.878 and a p value of 0.0003. Another example of the wearable device with a novel sleep monitoring method could be found in prior work (Weng et al., 2017). The authors monitored tongue base deformation during sleep to observe tongue base thickness changes (TBT) in patients with OSA. The device is composed of 3-MHz 16-channel custom-designed ultrasound transducers for ultrasonography. The device is placed underneath the chin to monitor the tongues during sleep. Simultaneous sleep measurement with PSG could show that TBT increased and remained elevated for few seconds before the beginning of hypopnea and apnea events. It also showed that tongue collapse during the hypopnea and apnea events occurred close to the tongue base and TBT increased by 6.1 mm on average. The author expects this method to understand further the mechanisms of OSA and the development of treatment strategies.

CONCLUSIONS AND OUTLOOKS

This review summarizes the most recent technology updates in wearable sensors and integrated portable electronics for sleep monitoring applications. To overcome standard PSG limitations and enable at-home sleep monitoring, recent advancements have come up with systems with novel functional materials, new sensing structures, and advanced data analysis methods within a minimized, less intrusive form factor. Many efforts have been made to translate the complicated, uncomfortable systems used in PSG to monitor various physiological parameters into unobtrusive and easy-to-use systems that every individual can use at home. Measuring different signals for sleep monitoring from the other non-standard body locations with a more familiar and comfortable sensor or device structure is attempted and validated through comparison with standard methods. Moreover, many new systems could incorporate miniaturized low-profile sensors together within a single device platform to enable portable, more accurate, and comprehensive sleep monitoring. Furthermore, new types of physiological signal measurement, such as EDA, are proposed and explored in sleep monitoring to provide unique perspectives to evaluate sleep. Finally, advanced signal-processing methods, such as machine learning, could be applied to analyzing measured sleep signals to automatically assessing sleep quality and detect any sleep disorders with high accuracy.

Although these mobile sleep monitoring devices still lack an independent validation process, recent studies show clinical applications related to sleep health. A recent report by Fagherazzi et al. analyzed data from 15,839 individuals who used Withings wearable devices, including a wristband that measures heart activity and movement (Fagherazzi et al., 2017). The researchers found that people with poor sleep quality were frequently young males with elevated heart rate and high systolic blood pressure. Sringean et al. analyzed the nocturnal movements of patients with Parkinson disease by using wearable inertial sensors, which could quantitatively demonstrate nocturnal hypokinesia in PD patients (Sringean et al., 2016). Finally, work from Agmon utilized a wristband-type actigraphy monitor that measures sleep efficiency, sleep latency, and sleep duration. This study analyzed 34 community-dwelling older adults' sleep quality and showed an association between the lower SE with a decrease in gait speed and increased gait variability under dual-tasking conditions (Agmon et al., 2016).

Besides wearables, there has been an effort to develop a non-wearable sleep monitoring system to minimize the interruption with the user's natural sleep behavior, which suffers from limited amount of measured information and sleep assessment accuracy. Two of the most pronounced examples in the market include

Beddit from Apple and S+ from ResMed. Beddit is a thin strip sensor placed under a bedsheet. Its embedded pressure sensor measures the heart (ballistocardiograph) and respiration rate and body movement to discriminate awake, light sleep, and deep sleep. A recent validation study compared the performance of Beddit with PSG over ten subjects, and the result showed poor agreement between them with Cohen's kappa of 0.101 on average (Tuominen et al., 2019). There is a continued effort to improve the accuracy and expand this on-mattress pressure sensor's capability with novel material, structure, and form factors (Zhou et al., 2020). Beyond non-wearables, the S+ device offers a non-contact sleep monitoring platform with its Doppler radar system to monitor breathing, body posture, and movement. An evaluation comparison study with PSG over 27 subjects showed similar or slightly better agreement (87.6%) with PSG than actigraphy (~85.1%) in sleep/wake detection. However, S+ still showed limited agreement when analyzing specific sleep stages (~65%) (Schade et al., 2019). Non-contact sleep monitoring systems based on Doppler radar are also being actively researched to measure more physiological information types and provide higher accuracy (Tran et al., 2019).

One of the conspicuous challenges faced by wearable sleep monitoring systems arises from our weak understanding of sleep and lack of precise assessment methods. Scoring of sleep staging and detection of sleep disorder events are still characterized by considerable uncertainty even with the standard methods. When a single-night sleep PSG data is evaluated by multiple sleep experts for five-stage sleep scoring, the inter-rater agreements are usually reported between 82% and 89% (Danker-hopfe et al., 2009) (Nonoue et al., 2017). Sleep monitoring with non-standard systems with fewer channels of signal measurement would not be any more reliable. This also poses a substantial challenge to developing and validating the new sleep signal analysis method that often requires accurate labeling of their training dataset. Improvements in accuracy and reliability of the new systems introduced here will follow suit the advancements in further understanding in neurological and physiological studies of sleep and more objective clarification of sleep evaluation method.

Moreover, when comparing the classification algorithm's performance for a multiclass unbalanced dataset such as sleep stages, choosing the right statistical metrics for evaluation is important to objectively represent the performance and enable fair comparison among different methods. Especially in sleep staging, where the gold standard is manual scoring whose reliability is still in question, using the term "accuracy" may be misleading when the expected outcome does not necessarily represent the true class. Several evaluation metrics are being used, including agreement rate, sensitivity, specificity, and F-measure. Among these metrics, Cohen's kappa coefficient is currently most widely used in sleep scoring. It is suitable for evaluating inter-rater reliability between classification results for unbalanced multiclass datasets while correcting the possibility of agreement occurring by chance (Gunnarsdottir et al., 2020). Because N1 and NREM1 are challenging to classify, NREM1 sensitivity has been used as a performance evaluator in some recent works. Some researchers claimed that using these metrics is still not reliable enough to determine the superiority of one system over another and proposed new metrics to evaluate and compare the performance of sleep staging systems (Melek et al., 2020).

Sleep is an essential part of our life, and maintaining good sleep quality is critical to sustain our daily lives and enhance well-being. Continuous sleep monitoring at home will be a starting point for maintaining good sleep quality. Despite the promising advancements in wearable sleep monitoring systems, we still need further technological advances in electronics miniaturization, sensor technology, and device integration and packaging within a more compliant and unobtrusive form factor. Quantitative evaluation of daily sleep will be the first step in enhancing sleep quality and mitigating sleep disorders and related diseases. Future advancements in sleep technologies will transform the current passive form of sleep into an active process to effectively boost our health and improve our quality of life.

AUTHORS CONTRIBUTIONS

S.K. and W.-H.Y. designed the manuscript. S.K. and H.K. prepared the figures. S.K. and W.-H.Y. wrote the manuscript. All read and approved the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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