Recent Advancement in Sleep Technologies: A Literature Review on Clinical Standards, Sensors, Apps, and AI Methods

GOZDE CAY1,2, (Graduate Student Member, IEEE), VIGNESH RAVICHANDRAN1, SHEHJAR SADHU1, (Student Member, IEEE), ALYSSA H. ZISK3, AMY L. SALISBURY4, DHAVAL SOLANKI1, (Member, IEEE), AND KUNAL MANKODIYA1, (Member, IEEE)

1Department of Electrical, Computer and Biomedical Engineering, University of Rhode Island, Kingston, RI 02881, USA
2Department of Surgery, Baylor College of Medicine, Houston, TX 77030, USA
3Interdisciplinary Neuroscience Program, University of Rhode Island, Kingston, RI 02881, USA
4School of Nursing, Virginia Commonwealth University, Richmond, VA 23284, USA

Corresponding author: Gozde Cay (gozdecay@uri.edu)

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ABSTRACT This is a literature review paper covering state-of-the-art sleep technologies to measure sleep and clinical sleep disorders. This paper addresses an interdisciplinary audience from a variety of subdomains in engineering and medicine. We reviewed 120 scientific papers, 15 commercial mobile apps, and 4 commercial devices. We selected the papers from scientific publishers including Institute of Electrical and Electronics Engineers (IEEE), Nature, Association for Computing Machinery (ACM), Proceedings of Machine Learning Research, Journal of Informatics in Health and Biomedicine, Plos One, PubMed, and Elsevier and Nature digital libraries. We used Google Scholar with keywords including “sleep monitoring”, “sleep monitoring technologies”, “non-contact sleep monitoring”, “mobile apps for sleep monitoring”, “AI in sleep technologies”, and “automated sleep staging.” The manuscript reviews sleep technologies, including sleep lab technologies such as polysomnography and consumer sleep technologies categorized as ambient room sensors, wearable sensors, bed sensors, mobile apps, and artificial intelligence. We primarily focused on validation and comparison studies of the reviewed technologies. The manuscript also provides an overview of several clinical datasets for sleep staging and taxonomizes the different learning methods. Finally, the manuscript offers our insights and recommendations about the application of the reviewed sleep technologies.

INDEX TERMS AI for sleep, sleep disorders, sleep interventions, sleep medicine, sleep monitoring, sleep sensors, sleep technology.

I. INTRODUCTION

Over the past few decades, sleep has received growing attention in research due to its importance in daily life, health and well-being, and medicine. Since the relatively recent discovery that rodents deprived of sleep for prolonged periods would eventually die, it became increasingly clear that sleep was critical not only to survival, but also to healthy human functioning [1], [2]. The physiological underpinnings of sleep processes are increasingly linked to physical and mental health as well as daily life performance at work, school, and sports. In essence, sleep is a core component of life. Understanding sleep through measurement has become a primary theme of modern technology.

In this paper, we aim to provide a literature review of technologies used to measure sleep as well as an understanding of general sleep principles and the components measured. Over 120 papers published in academic journals between 2011 and
2021 were reviewed. The papers were derived from Institute of Electrical and Electronics Engineers (IEEE), Nature, Association for Computing Machinery (ACM), Proceedings of Machine Learning Research, Journal of Informatics in Health and Biomedicine, Plos One, PubMed, Elsevier and Nature digital libraries, Google Scholar and mobile app marketplaces. Commercial devices, which were developed for different sleep monitoring techniques, were also included. The keywords were “sleep monitoring”, “sleep monitoring technologies”, “non-contact sleep monitoring”, “mobile apps for sleep monitoring”, “AI in sleep technologies”, and “automated sleep staging”.

This review paper is divided into several sections; Section II provides an overview of sleep focusing on the physiological and behavioral parameters measured in sleep. This section also discusses sleep development, as the measurement parameters may change over developmental stages. Lastly, this section provides an overview of sleep disorders and the relation to measurement needs in clinical research and practice. Section III presents the methods, tools, and technologies used to measure sleep. Section III presents a review of the sleep measurement technologies, divided into laboratory-based technologies including polysomnography and actigraphy and consumer-centered technologies including ambient room sensors, wearable technologies and mobile apps. In addition, Section III discusses several existing clinical datasets for sleep staging and taxonomized learning methods used for sleep staging. Section IV discusses future insights and recommendations about the application of the reviewed technologies to sleep research, clinical sleep, sleep disorders, and sleep interventions.

Our review process has observed a new trend that indicates that consumer sleep technologies (CSTs) are gaining popularity over laboratory-based technologies due to their user-friendly system and comfort in use. Studies show that consumer-centered technologies have the potential to be accurate and reliable. However, further technological validation studies with human participants are required to show the medical and clinical benefits and acceptability of CSTs.

II. UNDERSTANDING SLEEP

A. BRIEF HISTORY OF SLEEP

Prior to the 1950s, there was little interest in sleep in the scientific community. Most scientists presumed sleep to be a period of lowered brain activity that occurred when nighttime sensory stimulation was insufficient to maintain waking activity levels [3]. In the mid-20th century, however, it was discovered that sleep involves active processes, leading to additional questions about the nature of sleep [4]. Using such basic tools as direct visual observation and an Öffner Dynograph, Aserinsky & Kleitman documented the first modern evidence of rapid eye movements (REM) during sleep [5]. Their discoveries with a colleague, William Dement, over the next decade would link REMs to specific brain wave patterns, physiological processes, and dreaming, which sparked new interest in the study of sleep [3], [6]. Although this seminal work represents a major shift of interest in sleep science, it is important to note that Loomis was the pioneer to notice the distinct EEG patterns recognized as Non-Rapid Eye Movement (NREM) sleep, including vertex waves, slow oscillating delta waves, K complexes, and sleep spindles [7], [8]. These EEG patterns were classified into five stages of increasing sleep depth. This was later revised in 1957 when Dement and Kleitman proposed the addition of eye movement patterns measured with an electrooculogram to determine REM sleep, which was shown to alternate in a cyclical pattern with 4 stages of NREM sleep [6].

Brain wave frequencies and the presence of eye movements were found to be insufficient to consistently distinguish REM sleep from NREM stage 1 sleep (transitional wake to sleep period or drowsing) due to the presence of similar EEG frequencies and eye movements in both stages [9], [10]. Reliable differentiation was accomplished by noting the quality of eye movements (slow and rolling when drowsing vs rapid and jerky in REM sleep) and muscle tone in addition to brain wave patterns. In 1968, a formal manual was developed to guide sleep state classification from multiple streams of graphical data, polysomnography or PSG, which incorporated additional measures of behavior, physiology, and motor activity [11]. Behavioral measurements include direct visual observation, video recordings, or mechanical measurement of body, limb, eye and facial movements. Mechanical measurement of muscle activity is accomplished with an electromyograph (EMG), ocular movements are measured using an electrooculogram (EOG), and respiration is measured using a thermistor, pneumography, or pressure sensor. A more recent revision of the standards manual occurred in 2007, which consolidated NREM stages 3 and 4 into a single deep sleep stage and added evidence based decisions for respiratory events, arousals, and standardized epochs for scoring [12].

Discoveries over the following decades revealed that sleep is the observable result of coordinated neurological and physiological processes. These interrelated processes have both independent and environmentally cued circadian rhythms (oscillation of the sleep-wake cycle) and play a central role in the generation of ultradian rhythms (oscillation of distinct states within sleep) [13]. The circadian timing system consists of input from afferent pathways, such as those sent via the retina to the suprachiasmatic nucleus in response to light, which serves as a circadian pacemaker, which generates the oscillations, and output via efferent pathways. In the absence of environmental entrainment, the circadian rhythms continue with a slightly altered cycle length [4].

The ultradian system comprises the biological processes involved in the alternations of sleep states, typically in cycles of 90-120 minutes, during sleep periods [14]. Disruption of either circadian or ultradian rhythms results in sleep disorders, as will be described briefly in section D.

The history of sleep monitoring technologies is summarized in Figure 1.
B. STAGES OF SLEEP & PHYSIOLOGICAL CHANGES

With the development of polysomnography (PSG), which measures brain waves, heart rate, respiration, eye movements, and neck muscle tension, it became possible to determine sleep onset and to discover that sleep is composed of distinct stages [4]. As it became routine to record respiratory and cardiac variables during what would later be called PSG and patients presumed to have narcolepsy (often characterized as excessive drowsiness during the day followed by sudden attacks of sleep) were referred for sleep testing, it became apparent that sleep breathing disorders, such as obstructive sleep apnea (OSA), were causing overwhelming daytime sleepiness in many such patients [3].

The ultradian rhythms of sleep are often categorized into non-rapid eye movement sleep (NREM sleep) and rapid eye movement sleep (REM sleep), which cycle throughout the night. REM occurs approximately every 90 minutes in typical adult human sleep and, over the course of the night, the duration of each REM period increases [3]. Transitions between REM and non-REM sleep may be handled by mutually inhibitory areas in the mesopontine tegmentum, which create a flip-flop switch [15].

In REM sleep, overall activity in the brain can be greater than waking brain activity and therefore require greater blood flow. In tonic REM, blood pressure and heart rate are lower than in an awake state and are less responsive than normal to changes in blood flow requirements. In phasic REM, heart rate and blood pressure are highly variable. Breathing is largely under behavioral control in REM, with little dependence on carbon dioxide or oxygen levels in the blood. Temperature regulation essentially stops in REM sleep, though a person will wake and begin regulating their body temperature if they become too warm or too cold during REM sleep [4].

On a PSG, REM sleep is characterized by sawtooth waves of varying frequency, extremely low tension in the neck muscles, and bursts of eye movement. The low tension in the neck muscles is a result of the medulla inhibiting the nerves which cause muscle contractions, effectively paralyzing the sleeper [4].

In NREM sleep, cells in the basal forebrain dampen activity in the rest of the forebrain. Respiratory control is entirely automatic, varying with oxygen and carbon dioxide levels in the blood. Carbon dioxide levels maintained during NREM sleep are slightly higher than those are in waking, and oxygen levels may be slightly lower. Breathing is generally regular and rhythmic. Blood pressure and heart rate are also typically lower in NREM sleep than when awake. Body temperature is homeostatically maintained, but again at a slightly lower temperature than during wake. Throughout NREM sleep, neck tension is lowered in comparison to wake but not as low as in REM sleep [4].

NREM sleep can be further categorized into stage 1, stage 2, and slow-wave sleep (SWS). Stages 1 and 2 are characterized by the presence of sustained theta waves in electroencephalography (EEG) signal, with large, slow peaks followed by smaller valleys (K-complexes, Figure 1) and 0.5-1.5 second periods of 12-14 Hz oscillations (spindles) appearing in Stage 2. These spindles and K-complexes are produced by slow bursts of activity in the thalamus in NREM sleep. Theta waves dominate the EEG in the stages 1 and 2 and delta waves dominate the EEG in SWS [4].

C. SLEEP DEVELOPMENT

Sleep processes begin prior to birth and reflect developing neural activity. It is important to understand the changing dynamics of physiological systems as stable states emerge while measuring sleep. In the fetal period, the continuous
TABLE 1. Comprehensive list of sleep measurement indicators.

| Indicator     | Measurement Mode | Wakefulness                      | N1 Drowsy, Non-Alert | NREM Sleep | Sleep States | Transition              |
|---------------|------------------|----------------------------------|----------------------|------------|--------------|-------------------------|
|               | Direct or video  | Active                            | Quiet                |            |              | Sleep-Wake              |
|               | observation      | Awake                             | Awake                |            |              | Transition              |
| Eye Movement  | Yes              | EOG                              | Eyes open, scanning,| Eyes opening & 4 | None,      | None,                  | Intermittent             |
|               |                  |                                   | (unless crying)      | closing, rolling | eyes closed | eyes closed            | or steady, rapid,       |
| Motor Activity| Yes              | EMG, Actigraph, Thermal          | Little or none       | Little or none | None,      | none,                  | Intermittent             |
| Behavior      | Yes              | Large, sustained                  |                      | N/A        | No Deep/Quiet | Intermittent            |
| Respiration   | Yes              | Stretch, startle, movements       | Stirrles, small      | N/A        | Sleep       | Intermittent behavioral| Continuous              |
| Heart rate    | No               | Pressure, plethys, thermal       | Lower rate, decreased| N/A        | N/A         | Irregular              |
| EEG           | No               | ECG, Ballistocardiogram          | Highly variable rate | N/A        | Lower HRV, lower| Higher rate and         |
|               |                  |                                   | and HRV              | Spindle (12-15 Hz)| lower rate | HRV than NREM          |
|               |                  | Scalp electrodes, ear            | 2 - 7 Hr             | K-complexes | Slow oscillations | Increased               |
|               |                  | N/A                              |                      |           | Delta waves  |                        |

FIGURE 2. EEG signals of sleep stages 1 & 2, showing spindles and K-complex.

Fetal activity observed in the first trimester is gradually replaced by intermittent periods of rest, leading to alternating rest-activity periods [16], [17]. Motor activity cycles gradually become synchronous with fetal heart rate rhythms and acceleration patterns [18] that continue into the newborn period [19] and have been used to define fetal behavioral states [20], [21], [22], [23], [24]. Infant behavioral states were classically defined by the direct observation of coalescing behaviors into stable, temporary “states”. Observations included the eyes (movement, open vs closed, “alertness”), skin color, respiration (regular, irregular), muscle tone (high, low), specific movements (stretch, yawn, facial expressions, twitching, jerky limb movements, large and small limb movements, etc.), and vocalizations [25], [26]. EEG patterns reflecting specific sleep states are not well differentiated in the newborn [27], [28], and the most current recommendations are to identify periods of continuous vs. discontinuous EEG rather than...
specific EEG patterns for sleep states [29]. Reliance on other, less obtrusive measures is often preferable in the young infant [30]. Non-EEG methods have been shown to reliably determine sleep from the wake in infants and older children, particularly when combined with physiology, specific sleep states. Body movement alone measured by accelerometers (actigraphy) can distinguish patterns of sleep from wake [31], [32], while direct observation [26] or video-taped observation of behavioral measures [33], or body movement patterns coupled with respiration have been able to reliably measure specific sleep states [34], [35]. Table 1 summarises generally accepted guidelines for the measurement of sleep states.

D. SLEEP DISORDERS
1) PRIMARY SLEEP DISORDERS
Sleep problems may result from misalignment between a person’s occupational or societal obligations and their internal clock, a specific underlying sleep disorder such as sleep breathing disorders or narcolepsy, or other underlying medical conditions such as neurological issues, pain or heart related problems [36].

In particular, sleep apnea is estimated to affect 4-9% of the population, with 75% of these affected individuals remaining undiagnosed and untreated [37]. In sleep-disordered breathing, there may be decreased muscle tone surrounding the upper airway causing partial or complete airway blockage, as in hypopnea or OSA, and respiratory effort-related arousal (RERA). Thoracic and abdominal movement in opposite directions is a common, though not universal, pattern in obstructive respiratory events. The other possible cause for disordered sleep breathing is neurological, in which a patient partially or completely stops making thoracic and abdominal breathing movements. This is responsible for central apneas and hypopneas, as well as Cheyne-Stoke breathing. Finally, there may be mixed apnea and hypopnea, where cessation or reduction in movement appears first, followed by movement with characteristics of obstructive apnea or hypopnea [38].

Further, chronic neurological disorders, such as narcolepsy, can affect neural control of the sleep-wake cycle in uneven and interrupted sleep. Narcolepsy patients feel rested after waking but then feel sleepy throughout the day [3], [39].

In REM sleep behavior disorder, there is a failure of the atonic paralysis typical of REM sleep. The disinhibition of motor control in REM sleep permits a variety of movements, ranging from simple repetitive twitches to more complex and seemingly purposeful motor behaviors. These movements are typically called dream enactment behaviors [40], [41].

2) CONDITIONS AFFECTING SLEEP (SECONDARY SLEEP DISORDERS)
In addition to the primary sleep disorders, there are variety of conditions which may have a disordered sleep as a symptom, or as a side effect of treatment. For example, sleep disturbances are frequently reported in Parkinson’s disease. Excessive daytime sleepiness may occur in Parkinson’s, separate from fatigue, as a medication side effect or related to damage to the hypothalamic hypocretin system. Medication used in the treatment of Parkinson’s is generally fast-acting, with a distinct “on” and “off” phase. Nocturnal “off” symptoms often result in mobility related challenges in bed, which can cause difficulty turning in bed or attaining a comfortable sleep position. Restless legs syndrome may also correlate with Parkinson’s disease, with younger age and are less likely to have a family history than those with idiopathic restless legs syndrome [42]. Patients with Parkinson’s disease are more likely to suffer from REM sleep behavior disorder than the general population as well [43]. REM sleep behavior disorder is considered a prodromal stage for neurodegenerative alpha-synucleinopathies, of which Parkinson’s disease is one [40].

III. METHODS AND TOOLS FOR SLEEP MONITORING
A. CATEGORIZATION OF SLEEP MONITORING TECHNIQUES
Several methods and tools are used for sleep monitoring [36], [44]. Among these tools, laboratory polysomnography (PSG) is widely used for sleep monitoring and the identification of disordered sleep. Alternative tools have been explored to account for cost and location limitations and are often validated against PSG. Mobile and home-based technologies can shorten wait times and allow sleep to be monitored in the familiar home environment [36]. They can also be used to evaluate sleep and connect sleep patterns to subjective issues regarding sleep and daytime performance [36]. Different categories of sleep monitoring technologies are shown in Figure 3.

1) LABORATORY SLEEP TECHNOLOGIES
The laboratory based technologies include PSG and actigraphy. Both of these technologies are used under controlled lab settings for sleep monitoring. These technologies involve recording multiple physiological parameters (such as ECG, EMG, EOG, EEG) to monitor sleep quality and detect sleep disorders. The following sections discuss both of these technologies in more detail.

a: LABORATORY POLYSOMNOGRAPHY (PSG)
Laboratory PSG requires at least four electrical signals: at least one electromyography (EMG) channel to measure neck muscle tension, two electrooculography (EOG) channel to measure eye movements, and at least one electroencephalography (EEG) channel for neural activity signals [4]. However, this are a minimum requirements and recording of 1-3 EEG channels, 1-3 EMG channel, 2 EOG channels, an electrocardiography channel, 1-2 respiratory effort channels, a blood oxygen saturation channel, an audio channel (for snoring), and multiple body position/posture channels are typical [36]. Depending on a particular sleep study’s purpose, other sensors may also be included.

In a formal sleep study, EEG is taken from approximately 8 cm above an ear and from the back of the head, respectively
corresponding to the 10/20 EEG channels C3 or C4 and O1 or O2. Dead skin and oils may be removed from the scalp at these EEG locations to improve electrical reception. EEG electrodes are also filled with an electrolyte gel before placement [3].

EOG, taken at the outer corners of each eye, measures eye movements using the slight positive charge of the front of the eye. EOG signals resulting from eye movements resemble mirror images of each other, while signals which do not resemble mirror images are affected by other sources [4], [45].

EMG records electrical activity related to muscle activation, taken below the chin or jaw to measure tension in the neck. This indicates sleep and sleep stage, as neck muscles maintain high tension to hold the head up when awake, are almost totally relaxed in REM sleep, and are moderately relaxed in NREM sleep [4], [46].

Heart rate may be measured in several ways. In PSG, an electrocardiogram (ECG) is typically taken. While PSG sleep staging is typically based on EMG, EOG and EEG, information about sleep architecture and efficiency, as well as arousals and respiratory function, can be gained from the ECG [4], [47].

When measuring sleep, it is crucial to identify the instance of initial sleep onset, final awakening, and transitions between different sleep stages. Determination of initial sleep onset poses some difficulty, as the transition is slow. Rather than dropping off immediately, there is a period of relaxed drowsiness, and people often transition in and out of sleep several times before remaining asleep. Most criteria for determining sleep onset include the presence of sustained, low intensity 3-7 Hz theta waves (in the EEG recording) and other indicators of sleep stages 1-2 [4].

In addition to EEG, EOG, and EMG, other types of measurements may provide additional information. Low-resolution near-infrared video, often 160 x 120 pixels, has traditionally been used in sleep studies [48].

Since PSG records cardiorespiratory, neurophysiological, and other physical and physiological parameters during sleep, which allows doctors or researchers to understand the functioning of multiple organ systems and their contribution in wakefulness and sleep stages [49]. Different studies evaluate the clinical usefulness of PSG in various disorders included but not limited to epilepsy, hypnic headache syndrome, OSA, obesity, and insomnia [50], [51], [52], [53], [54].

b: ACTIGRAPHY

Actigraphy, a method used to track to sleep for more than 20 years, uses devices that can be placed on the ankle, trunk, or most commonly the wrist to monitor movement. Actigraphy data is analyzed to measure activity or inactivity and determine wake/sleep stages. Its accuracy is evaluated in comparison with PSG, observations, sleep logs and diaries, Multiple Sleep Latency Tests (MSLT) and EMG. Actigraphy is used in the diagnosis and assessment of insomnia, including insomnia secondary to circadian rhythm disturbances, disturbed sleep in children, sleep-related breathing disorders, and restless leg syndrome. A clinical practice guideline was also developed by the American Academy of Sleep Medicine [55]. The disadvantage of actigraphy is its reliance on a single type of data [56]. In addition, since actigraphy depends on measuring physical activity, it is not useful to monitor sleep patterns for individuals experiencing long periods of wakefulness without any motion [57].

2) CONSUMER SLEEP TECHNOLOGIES

Despite the status of sleep lab PSG as the “gold standard” for sleep monitoring, it has limitations. Correlation between objective measures of severity in sleep-disordered breathing, including OSA, is relatively weak [58]. In addition, many sensors involved in PSG may interfere with sleep, particularly sleep in a prone position [38], [59]. Parents of preschoolers in overnight sleep studies often report that the child’s sleep in the lab was atypical [60]. The removal of patients from their regular sleeping environments is a potential source of bias in sleep studies [61]. Overnight sleep studies in the lab also require significant resources, which impedes many in obtaining sleep studies [58]. On top of this, diagnosis for conditions such as
insomnia, insufficient sleep, and circadian rhythm disorders requires several nights of monitoring, reducing the utility of a single night’s lab sleep study for these conditions [36].

Home sleep testing already sees frequent use to confirm OSA. In some cases, a regular polygraph is sent to a patient’s home with instructions, allowing patients to test themselves at home and send their results for interpretation. This allows evaluations lasting multiple nights and keeps patients in their home sleeping environments, though it still involves several contact sensors [36].

For these reasons, it is important to find affordable and less resource-intensive methods than PSG for monitoring sleep. Research is ongoing to explore different sleep monitoring solutions, involving contact and non-contact sensors. Room sensors, wearable technologies, mattress-based pressure sensors, and mobile applications are all studied as sleep monitoring tools [38], [48], [59], [60], [62], [63], [64], [65], [66], [67], [68]. In some cases, these methods are based on a subset of signals and/or sensors used in PSG, with the number of sensors significantly reduced to make monitoring more accessible to patients at home [38].

A variety of options are similarly available to consumers, again covering wearable technologies, mattress-based pressure sensors, and mobile applications. While some options make validation studies available, many consumer sleep monitoring solutions do not provide this information [61], [69]. In other cases, information is available but not entirely favorable [70], [71].

a: AMBIENT ROOM SENSORS

Ambient room sensors are sensors or devices which are placed in the room, preferably near the bed. They mainly monitor body movements and breathing rate to extract sleep information. One of the key advantages of using such sensors is that they do not require any wearable device on the body. Wi-Fi-based devices, radio signals based devices, camera-based systems are some examples of ambient room sensors.

i) COMMERCIALY AVAILABLE AMBIENT ROOM SENSORS

S+ by ResMed Sleep Tracking is a non-contact sleep monitoring device developed by ResMed [73]. It monitors upper body movement (chest expansion and relaxation), and the device software combines respiration and body-movement signals. It additionally monitors environmental light, noise, and temperature then synchronizes them through the companion smartphone app. The app evaluates environmental conditions and provides feedback on how to improve sleep routines and conditions. Chung and colleagues used the S+ device to validate their sleep stage classification algorithm [74]. Their classification algorithm also depended on fusing data from multiple sensors, specifically non-contact microphone sensors and radar sensors. While the radar sensor was used to monitor wake-related limb movement, heart rate and breathing rate, the microphone was used to monitor sleep sounds, including snoring and breathing. They compared their results with S+ device results and found that their algorithm showed 64.4 percent accuracy in detecting sleep stages.

ii) RESEARCH ON AMBIENT ROOM SENSORS

One non-contact monitoring method is using Wi-Fi signals to monitor the human body. The studies which use Wi-Fi, use a pair of off-the-shelf Wi-Fi devices, collect Channel State Information (CSI) from those devices by measuring the Wi-Fi signal reflected from static objects and body movements, and then extract sleep data from CSI. These sleep data include different sleep positions (foetus, log, yearner, soldier, freefaller, starfish), postures and body movements [72], [75], [76]. The studies in this area showed that extracting and classifying body movements and and stationary postures resulted with accuracy over 90% [75], [76].

Another frequently used technique is using radio signals to monitor sleep and the human body. Two radars were used in those studies, and the signals reflected from the human body were analyzed to extract sleep information including but not limited to breathing rate, heart rate, people’s location, bed location, posture, sleep latency, total sleep time, time of bed entry and exit, sleep efficicacy, and sleep quality [77], [78], [79], [80], [81], [82]. It was seen that the accuracy of detecting sleep status was varying between 85% and 99% [78], [79], [80], [81].

There are also methods that use sound, ambient light, camera systems, and accelerometer and motion sensors for sleep monitoring [83], [84], [85], [86], [87]. It is seen that extracting the sleep stages from breathing sound using a non-contact microphone reached 87% accuracy [83]. For camera-based measurement, the studies showed that a typical laptop camera can detect the overall sleep stage with 70.3% accuracy while a thermal and near-infrared imaging-based techniques can detect the breathing rate and heart rate during sleep with 95% accuracy [84], [85].

In addition, some studies evaluated commercially available devices such as Microsoft Kinect v2 sensor and SleepMinder [88], [89] and developed algorithms to increase their efficiency to monitor the sleep.

b: WEARABLE BODY SENSORS

The wearable sensors are the portable modules that can be attached to the body and are generally designed to be on the wrist, finger, feet, head, chest, or waist. They monitor the...
heart rate and body movements to extract the sleep information. Some of them also monitor the breathing rate. Smartwatches, such as Fitbit, Samsung Watch, Apple Watch, and others, are also included in this category.

i) COMMERCIALY AVAILABLE SLEEP SENSORS

Oura Ring was developed by Oura Company. It monitors sleep by monitoring different parameters such as heart rate variability (HRV), respiratory rate (RR), body temperature, resting heart rate (RHR), and movement [91]. The ring consists of a 3D accelerometer, a temperature sensor, and a photoplethysmogram (PPG). Oura claims that the ring determines sleep patterns according to changes in the body’s signals. The ring connects to a smartphone app to visualize the data and show the report to the users. Koskimäki and colleagues used the Oura Ring for their case study to study sleep duration and quality [92]. They collected data from 9333 Oura Ring users then chose 2170 very good sleepers. Then they focused on a single very good sleeper’s daily data. As a result, they came up with that lack of sleep consistency correlated with shorter sleep duration and lower sleep efficiency.

SmartSleep Deep Sleep Headband is, as the name suggests, a headband developed by Philips [93]. The headband monitors sleep and is also a recommendation system for improving sleep. It detects the “deep sleep” stage, then triggers quiet audio tones to improve sleep quality. They claimed that these tones help boost deep sleep waves. The company recommends the headband to people seeking to reduce daytime sleepiness, boost alertness and increase energy. They also say that it is not appropriate for people who have existing sleep conditions or are looking for help falling asleep. The headband connects to the SleepMapper smartphone app, which shows sleep patterns and any slow-wave boosts.

Go2Sleep was developed by Sleepon Company [94]. It is a wearable device with a silicone ring. Go2Sleep monitors sleep by monitoring the heart rate and blood oxygen level with a PPG sensor. By measuring these two vitals, it provides information about sleep quality and apnea screening. It is integrated with SleepOn smartphone app, and a comprehensive report consisting of sleep debt, toss and turn, AHI, blood oxygen, and heart rate is shown to the users. It also gives a physical alert to the users whenever the apnea is detected by vibrating.

ii) RESEARCH ON COMMERCIAL WEARABLE SENSORS

While smartwatches can be considered as a subset of wearable sensors, there is a sufficient variety of band-based sleep monitoring options to consider them separately. Some of the studies compared the commercial smartwatches such as Fitbit Ultra and Fitbit Charge 2 with PSG, actigraph and other commercial portable sleep monitors [95], [96]. Results showed that the accuracy of the smartwatches were more than 80% and the smartwatches were chosen by the users more [95], [96]. Empatica E4 and Bodymedia SenseWear Pro Armband were other wrist-worn physical sensors which were validated [97], [98].

There are also studies which developed a smartwatch with accelerometer, gyroscope, orientation sensor, microphone and ambient light sensor and detected the sleep postures with over 90% accuracy [99]. It was also seen that smartwatch could be used to monitor stress and sleep related problems so it could help the nurses for the patients with Behavioral and Psychological Symptoms in Dementia (BPSD) [100].

It was also seen that in-ear electroencephalogram (ear-EEG), magnetometer sensor on a chest belt, inertial sensors on trunk and forearms, printed electrode arrays, textile capacitive sensors on an ankle band, electrocardiogram (ECG) on a chest belt and GSR sensor on a wrist band were used to classify the sleep and sleep stages [90], [101], [102], [103], [104], [105].

C: BEDDING-BASED SLEEP MONITORING SYSTEMS

Pressure sensors embedded in mattresses, mattress covers, or mattress inserts have been used in several commercial sleep monitoring solutions, as well as in research applications. These systems have the benefit of unobtrusiveness, in that they do not directly contact the subject. This contactless approach is advertised as a feature for some sleep monitors. Mattress sensors typically claim the ability to detect respiration and heart rate based on changes in pressure from respiratory and cardiac movements.

i) COMMERCIAL BEDDING-BASED SLEEP MONITORING SYSTEMS

Among many commercially available systems,Tanita Sleep Scan SL-501 is a mat-based sleep monitors. It measures body motion, respiration rate, and pulse rate. It analyses the number of awakenings, time to get to sleep, and sleeping time with those data. [107].

Withings Sleep is another mat that analyses sleep duration, continuous and average heart rate, sleep onset and time to wake, snoring duration, and sleep quality score. It connects
with a mobile app (Android or iOS), which shows these sleep scores. It also controls the home automation system such as temperature, light, and other home-enabled devices [108].

Sonomat Company offers a continuous monitoring solution with a non-contact sensor array embedded into a mat that analyses sounds recorded using a stethoscope. Sonomat monitors body movements, detects apneas, and measures breathing sounds [69], [109].

Beddit is a system, which monitors sleep, snoring, heart rate, and breathing [110]. The system is designed as a belt-shaped sensor grid with piezo force, capacitive touch, humidity, and temperature sensors. For sleep monitoring, it analyses sleep time, bedtime, time to fall asleep, time awake, time away from the bed, wake-up time, and sleep efficiency. Beddit also analyses the average, maximum, and minimum heart rate and average breathing rate. It is compatible with iOS and watchOS apps. The app supports educational videos, Data analytic, weekly reports, bedtime reminders, morning results, tip notifications, goal setting for bedtime and sleep time.

RestOn Sleep Monitor is another belt-based monitoring system from Sleepace Company [111]. It monitors heart rate, respiration rate, sleep cycle, temperature, and humidity. It is compatible with iOS and Android apps. The app shows the sleep score, sleep time and duration, and the number of awakenings turns, and/or bed departures. It also indicates respiratory and heart rates. Moreover, the app has a smart alarm called Nox, which wakes the user at the lightest part of their sleep cycle.

The level of validation available for these devices in research and review papers varies greatly. The Sonomat has been compared to PSG with a sample of 54 subjects with OSA and eight healthy controls, with sensitivity to respiratory events found to be similar between the two monitoring options [69]. The Beddit made sensor validation data available but did not compare results to other sleep monitoring methods [112]. Other mattress solutions, such as the Tanita Sleep Scan and the RestOn mattress band, may not make validation data available [88]. The RestOn mattress band claims to be able to benchmark medical devices, but the data behind this claim does not appear to be available. Papers discussing the device instead discuss it in the context of reviewing sleep monitoring technology or announcing its release as a non-contact option for sleep monitoring.

d: MOBILE APPS FOR SLEEP MONITORING

With the ubiquity and versatility of mobile technology, including bedroom presence and use as an alarm clock, it is natural to consider its use for sleep monitoring [36]. As it stands, many mobile apps are available for monitoring sleep. Many of the apps take advantage of internal accelerometers for the purpose of actigraphy or the internal microphone to record snoring, while others depend on questionnaires [61], [71]. However, there is limited support for the validity of most commercial sleep monitoring applications. In particular, applications tend not to provide details about the specific data they collect or about the algorithms used, which makes attempts at validation more difficult [61], [70].

i) COMMERCIAL MOBILE APPS FOR SLEEP MONITORING

There are about 249 apps in Android’s Google Play Store and 212 apps on Apple’s AppStore [as of July 3, 2020] that are a mixture of health tracking, fitness tracking, meditation, and sleep recording apps. We decided to choose the apps, focusing only on sleep monitoring and showing sleep patterns to the users for this review paper. In addition, we decided on the apps, which work standalone, without requiring any other sensor except smartphone sensors. Therefore, fifteen apps were selected in this review, and they are summarized in Table 2.

From the above study survey of smartphone applications in both iOS and Android, we can observe eight applications from the total 15 studies that do not require additional hardware other than a smartphone. Three out of the 11 applications have performed clinical studies to validate
TABLE 2. Summary of mobile apps.

| App                          | Features offered by the app                                                                                           | Technology                                                                                                                                  | User review count | User rating count | Scientific study |
|------------------------------|------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------|-------------------|-------------------|-------------------|
| Sleep Analyzer[122]          | Sleep movements monitoring and smart alarms                                                                         | Not available                                                                                                                                 | Android: 2513      | Android: 3.2       | No                |
| Sleep Time+[123]             | Sleep movements monitoring and smart alarms                                                                         | Phone motion sensor based actigraphy                                                                                                        | Android: 410       | iOS: 4600         | No                |
| Sleeppace[121]               | Sleep monitoring, sleep-aid, smart alarm, and customized ambient scenarios                                             | Not available                                                                                                                                 | Android: 496       | iOS: 24           | No                |
| SleepScore[124]              | Sleep staging, personalized goal recommendations, Smart alarm, Sleep-aid                                               | Phone based noncontact sonar or hardware sensor ResMed sleep tracker                                                                         | Android: 412       | iOS: 5000         | No                |
| Sleep Theory[125]            | Smart alarm, Snore sensing, sleep and heart rate monitoring                                                          | Microphone audio analysis for snoring breathing and phone motion sensor actigraphy                                                           | Android: 1092      | iOS: 2            | No                |
| Sleep Cycle App[126]         | Sleep patterns and sleep quality monitoring                                                                        | Phone motion sensor based actigraphy                                                                                                        | Android: 119664    | iOS: 254200       | Yes[127]          |
| Sleep Tracker from Uvo[128]  | Different alarms, sleep quality and sleep efficiency monitoring                                                        | Uses heart rate measured from a compatible fitness band or smartwatch                                                                         | Android: 209       | iOS: 29           | No                |
| Sleepic[129]                 | Sleep monitoring, snoring analysis                                                                                   | Microphone audio analysis for snoring breathing and phone motion sensor actigraphy                                                           | Android: 19415     | iOS: 2100         | No                |
| Sleeprate[130]               | Snoring sensing, Smart alarm, sleep monitoring                                                                       | Phone motion sensor based actigraphy                                                                                                        | Android: 390       | iOS: 45           | Yes[131]          |
| Sleep as Android[132]        | Smart alarm, sleep monitoring                                                                                        | Not available                                                                                                                                 | Android: 321921    | Android: 4.5      | Yes[133]          |
| Sleep Tracker[134]           | Sleep and snoring monitoring, smart alarm                                                                          | Microphone audio analysis for snoring breathing and phone motion sensor actigraphy                                                           | Android: 7         | Android: 3.4      | No                |
| Sleepezi[135]                | Automatic sleep detection, Smart alarm, sleep cycle tracking                                                        | Phone motion sensor based actigraphy                                                                                                        | Android: 10        | iOS: 8            | No                |
| Sleep Debt Tracker[136]      | Sleep cycle tracking, smart alarm                                                                                   | Sleep tracking through phone microphone                                                                                                       | Android: 10        | iOS: 8            | No                |
| Sleep Monitor[138]           | Automatic sleep detection, Smart alarm, sleep cycle tracking                                                        | Not available                                                                                                                                 | Android: 307       | iOS: 171000       | No                |

their approach. Smartphone applications primarily use actigraphy and microphone audio analysis to perform sleep tracking due to their commonality across different smartphones across generations. These applications however, offer different smartphone placement suggestions for sleep tracking, such as under pillow, adjacent to the shoulder. The variability in sleeping configurations and user placement along with environmental sleep conditions reduce the validity of these sleep scoring systems. These applications however, still have a significant value from an accessibility point of view and enable users to easily monitor their sleep quality longitudinally.

ii) RESEARCH ON MOBILE APPS FOR SLEEP MONITORING

Most of the monitoring systems mentioned in Section 3.b.iii also have mobile applications for recording the data coming from different sensors and visualize the data to the users. Besides those applications, there are also research studies focusing only on smartphone sensors and smartphone applications for sleep monitoring.

Some research on the mobile apps focused on collecting data from mobile phone’s light feature, phone usage feature, stationary feature, and silence feature and trained their algorithm to estimate the sleep duration from these data [63], [139]. Another technique for collecting data was based
TABLE 3. Public datasets for sleep staging.

| Dataset Name                      | Sensing Parameters | Reference Method | No of Participants | No of Hours | Age Demographic | Health Condition | Dataset Filetype          | Study Reference |
|----------------------------------|--------------------|------------------|--------------------|-------------|-----------------|------------------|-------------------------|-----------------|
| RF-Sleep Sleep-EDF               | Radio band energy spectrum PSG | 3-channel frontal EEG Manual Scoring | 24                  | 750          | Young           | Healthy            | Plain text (.txt)       | [146]           |
| Montreal Archive of Sleep Studies (MASS) Dataset | PSG               | Manual Scoring   | 44                  | 220          | 21-101 (Young & Old) | 77 subjects Without Medication & 22 subjects with temazepam medication and placebo | European Data Format (EDF) | [147]           |
| ISRUC-SLEEP Dataset              | PSG               | Two Human experts scored | 200                | 1907         | 18-76           | 200 Healthy Individuals | EDF++               | [148]           |
| Physionet 2018                   | PSG               | Expert annotated | 100                | 944          | 22-85           | 40 Individuals with suspected sleep disorders | REC                   | [149]           |
| Cyclic Alternating Pattern (CAP) dataset St. Vincent’s University Hospital / University College Dublin Sleep Apnea Database (SVUH-UCD) | PSG & 3-channel BCG | Expert annotated | 1985                | 12295        | 55 years mean   | 1985 Individuals suspected with sleep disorders | WFDB (Physionet) | [150]           |
| St. Vincent’s University Hospital / University College Dublin Sleep Apnea Database (SVUH-UCD) | PSG               | Expert annotated | 108                | -            | 14-82           | 16 healthy individuals and 92 sleep disorder individuals | EDF                   | [151]           |
| St. Vincent’s University Hospital / University College Dublin Sleep Apnea Database (SVUH-UCD) | PSG               | Expert annotated | 25                  | 294          | 28-68           | 25 Individuals with suspected sleep disorder | EDF                   | [152]           |

on the smartphone’s microphone, ambient light sensor and accelerometer [140]. There were studies which also include daily sleep diary to classify good and poor sleepers [141] and accelerometer to include body movements [142]. Sonar-based system was another technique. In this system, the abdomen and chest movements were monitored with measuring emitted and reflected frequency-modulated sound waves [143]. In addition, there were studies which uses phone or external sensors to collect data and provide recommendations from medical professionals [96], [144], [145]. The results showed that the accuracy was varying between 80% and 90%.

In the comparison between commercial sleep tracking apps and scientific research based on mobile apps, we made important observations. Commercial sleep tracking apps are often lacking scientific evidence of how their claim on features they offer. For example, they mostly rely on accelerometer data to predict sleep parameters, including sleep timing, sleep quality, sleep staging, wake-up mood, etc. On the other hand, mobile apps developed through research provide an understanding of how the technology works, how it was studied on human participants, and what advantages and limitations it owns. It is a general understanding from user ratings that educated users who are very interested in improving their sleep quality tend to review the app based on its origin in science and research. Commercial sleep tracking apps rely on testimonials from their customers that are subjective and cannot provide scientific verification.

e: ARTIFICIAL INTELLIGENCE (AI), DEEP LEARNING AND SIGNAL PROCESSING IN SLEEP STAGE MONITORING TECHNOLOGIES

Traditional polysomnography (PSG) based sleep staging requires manual scoring of the multichannel physiological signals by an expert. A class is assigned for 30-second segments (epoch) as either wake, REM sleep, NREM sleep (N1, N2, N3). This process is highly repetitive and time-consuming and needs to be performed for the entire sleep period for the assessment adding to the cost of diagnosis. Further, if multiple sleep staging experts rate PSG, inter-rater variability arises, adding additional complications to the diagnosis process. Recent developments in wearables, ambient sensing techniques, and data-driven learning methods have been applied to perform automated sleep scoring. This section is broadly divided into four categories: 1) Dataset: In this section, we present the publicly available sleep data sets. 2) Feature-based learning methods: These methods use signal processing feature extraction techniques to classify sleep stages. 3) Deep learning-based methods: They use automated classification techniques eliminating the need for feature extraction to classify sleep stages. 4) Research on both sensors and classification: We describe the combination of sleep sensors and classification methods.

i) PUBLIC DATASETS FOR SLEEP STAGING

Automated sleep staging approaches are largely motivated by the increased amount of publicly available datasets available for analysis with expert sleep scoring. These datasets
usually record polysomnography rhythms that are the key measurement parameters or for expert scoring along with additional measurement approach to validate against the gold standard that is expertly scored Polysomnogram. With the advent of low-cost biophysiological monitoring hardware, ease of availability of wearable sensors along with ambient sensors, it is now possible to perform longitudinal monitoring of patients with sleep issues from the comfort of their own

| Study | Input Signal | Public Dataset/In-house | Learning Method | Features Used | Population Size | Study Population | Reference Method |
|-------|--------------|-------------------------|-----------------|---------------|-----------------|-----------------|-----------------|
| Lajnef et al. [153] | PSG | In-house | SVM | Time Domain: Linear prediction, Variance, RMS, Skew, Kurtosis coefficient, etc. Frequency Domain: Spectral Power, Spectral Entropy Time Domain: Peak to peak amplitude in EOG, Hjort parameters, etc. Frequency Domain: Relative Spectral power, Slow wave index etc. Time-Frequency Domain features: Maximum Overlap Wavelet Transform [Energy, Mean, Std deviation] | 15 | Healthy | Expert annotation (R&K guidelines) |
| Khalighi et al. [154] | PSG | ISRUC-Sleep | SVM | Time Domain: Skew, Kurtosis, Hjort Frequency Domain: Relative band power, Power ratios, Edge frequency, Spectral entropy | 40 | Healthy & Individuals with sleep disorders | Expert annotation (AASM guidelines) |
| Mikkelsen et al. [155] | Ear-EEG | In-house | Random Forest | Time Domain: Zero Crossing rate, First to fourth order moments, etc. Frequency domain: Spectral band power, Spectral edge frequency, Spectral entropy etc. Non-linear: Appropriate entropy, Correlation dimension, Higuchi fractal dimension etc. | 15 | Healthy | Expert annotation (AASM guidelines) |
| Nakamura et al. [156] | Ear-EEG | In-house | SVM | Multi-scale Permutation entropy, spectral edge frequency | 22 | Healthy | Expert annotation (AASM guidelines) |
| Kolcy et al. [157] | C4-A1 EEG channel | In-house | SVM (ensemble) | Time domain: Zero Crossing rate, First to fourth order moments, etc. Frequency domain: Spectral band power, Spectral edge frequency, Spectral entropy etc. Non-linear: Appropriate entropy, Correlation dimension, Higuchi fractal dimension etc. | 28 | Healthy & Individuals with sleep disorders | Expert annotation (R&K guidelines) |
| Bozkurt et al. [158] | PPG | In-house | kNN, SVM | Time Domain features: Mean, SD, Skew, Kurtosis, Hjort parameters, etc. Frequency Domain features: Band energy Peak-to-Peak amplitude, interquartile range, skewness, kurtosis, signal power etc. | 10 | Individuals with OSA | Expert annotation (AASM guidelines) |
| Khademi et al. [159] | Accelerometer | In-house | Random Forest, Naive Bayes, Logistic Regression | Peak-to-Peak amplitude, interquartile range, skewness, kurtosis, signal power etc. | 81 | Healthy & Individuals with sleep disorders | Expert annotation (AASM guidelines) |
FIGURE 7. Example of mobile apps [121].

home over a brief period in a sleep lab. The large size and volume of such datasets enable the use of learning-based sleep staging methods.

We introduce a number of publicly available datasets (Table 3). These datasets were used in a number of papers we discuss below.

**ii) FEATURE-BASED SLEEP STAGING METHODS**

Feature-based learning methods require the extraction of features which represent relevant attributes derived from raw sensor data. The features can be obtained by applying various nonlinear, time-frequency domain, frequency domain, and time domain functions on the sleep signals before being provided to a classifier to determine sleep stages. A wide range of machine learning classifiers is used in sleep staging from Logistic Regression, k-nearest neighbour, random forest and support vector machines (SVM). For example, Lajnef et al. proposed a decision tree-based Support Vector Machine classifier using time and frequency domain features extracted from EMG, EOG, and EEG signals recorded using polysomnography to perform hierarchical sleep staging from Awake or Sleeping to REM to NREM [153]. This work improved execution time and performance enhancement using the dendrogram approach for classification of sleep stages.

Researchers also used different combinations of PSG channels by extracting a variety of features including peak-to-peak amplitudes, spectral power and energy & mean features obtained from Maximum Over- lap Wavelet and performed a comparison study [154]. This comparative study reported that an acceptable tradeoff was obtained using 1 EMG channels, 2 EOG channels, and 3 EEG channel [154].

Studies also explored data collected from ear location for sleep stage classification. A Random Forest classifier combining time-frequency, only frequency, and only time domain features extracted from EEG was explored by Mikkelsen et al [155]. Additional features were extracted from the pseudo EOG and EMG proxies derived from the Ear-EEG signal after extraction. This study evaluated an alternate measurement EEG measurement site, like ear- EEG, for sleep staging over the automated PSG. Another study also proposed a wearable in-ear EEG monitor with two data channels aiming to optimize the number of data channels for sleep stage classification along with PSG expert scoring for reference [156].

Researchers also proposed using a variety of time and frequency domain features, including nonlinear features like Appropriate entropy and Correlation dimension using an ensemble of five parallel binary SVM classifiers for each sleep stage [157][154]. The proposed ensemble model was validated with experts’ annotations according to R&K Guidelines with PSG. The ensemble approach resulted in the selection of an optimal feature subset resulting in improved performance. Another study proposed using features extracted from photoplethysmogram, and heart rate variability [158]. The study investigated if HRV and PPG signals could provide acceptable performance for identification sleep stages.

In another study a binary sleep-wake classification was achieved using wrist actigraphy involving features such as signal power, kurtosis, skewness, interquartile range, and peak-to-peak amplitude extracted from accelerometer signals; the results were compared with an expert scored PSG [159].

Overall, in our literature review we found that studies using signal processing based feature extraction and machine-learning techniques were more commonly found with in-house studies compared to approaches using public datasets.

**iii) DEEP LEARNING-BASED SLEEP STAGING**

Several researchers explored deep learning-based approaches for identifying various sleep stages including REM, N1, N2, N3 and W stages [160], [161], [162], [163], [164], [165]. Mousavi and colleagues proposed an automated sleep staging annotation method SleepEEGNet [160]. SleepEEGNet uses one channel Electroencephalogram (EEG) signal to classify
TABLE 5. Summary of deep learning based sleep staging research.

| Model Name       | Year | Model overview                                      | Accuracy | Github                        |
|------------------|------|----------------------------------------------------|----------|-------------------------------|
| SleepEEGNet[160] | 2019 | CNN + BiRNN + Encoder decoder blocks               | 84.26%   | https://github.com/MousaviSajad/SleepEEGNet |
| U-time[161]      | 2019 | CNN encoder-decoder blocks + Segmentation classifier | 79%      | https://github.com/perslev/U-Time |
| SleepStageNet[162] | 2019 | CNN+RNN+Conditional random fields                  | 80%      | Not available                 |
| SeqSleepNet[163] | 2019 | CNN + Expert features + LR + DT + GBT              | 87.1%    | https://github.com/pquocchuy/SeqSleepNet |
| SLEEPER[164]     | 2019 | CNN+ Expert rules                                  | 85%      | Not available                 |

five sleep stages (i.e., REM, N1, N2, N3 and W). The proposed model achieved an overall accuracy of 84.26%. In another study Perslev and colleagues proposed a U-Net inspired encoder-decoder model, i.e., U-time, to automatically classify the five sleep stages, namely REM, N1, N2, N3 and W [161]. This study compared performance of proposed method with a baseline of a reimplemented CNN-LSTM network called DeepSleepNet. Researchers explored interpretable deep learning model in combination with machine learning models [164]. This approach fused expert-defined rules as features and deep learning models. Using this method five sleep stage (N1, N2, N3, REM and Wake) sleep classification was achieved. Phan et al. developed an end-to-end hierarchical attention based bi-directional recurrent neural network to classify five sleep stages [165] and joint classification and prediction framework for classifying sleep stages [163]. Three PSG channels, namely EEG, EOG, and EMG, were used for classification. Chen and colleagues proposed a Multiscale Convolutional neural networks combined with RNN and Conditional Random Field for capturing contextual information and classifying the sleep stages using EEG [162]. Output included Wake, REM, Light sleep, Deep sleep classes. The results concluded that the Fpz-Cz channel had 0.88% accuracy, and the Pz-Oz channel performed with 0.85%. Zhao et al. proposed a combined CNN-RNN network to predict sleep stages [146] that used radio frequency signals to extract time-invariant features reducing the need for other devices.

iv) RESEARCH ON BOTH SENSORS AND CLASSIFICATION

Researchers also developed sensor technology and applied AI-machine learning techniques on sensor collected data. Walsh and colleagues developed an under-mattress bed sensor (UMBS) system to show sleep/wake discrimination [115] [112]. They used four classifiers (SVM, non-linear artificial neural network (aNN), k-nearest neighbor (kNN), and linear and quadratic discriminant analysis (LDA and QDA)) to differentiate wake and sleep events. In another research, Laurino et al. developed a prototype Smart-Bed to monitor subject movement and position, physiological signals, and environmental parameters [119] [116]. A frequency spectrum-based approach was used to estimate the breathing rate. An artificial neural network was used for classification using polysonomgraphy, electroencephalography, electrocardiography, respiratory airflow, snoring, electromyography, and oxygen saturation data.

IV. DISCUSSIONS & FUTURE INSIGHTS OF SLEEP TECHNOLOGIES

This review encompasses a wide range of sleep technologies that are either commercially available or in the research for validation and testing. PSG in sleep labs monitors the sleep and offers to study the majority of the sleep disorders but is still limited by discomfort posed by bulky devices and wires dangling from the body and head. To increase the comfort of the patients and participants, there is a strong need for a natural setup in which participants are welcomed and can have a natural sleep cycle. Wireless PSG is one of the future technologies that can overcome several limitations and will require substantial innovation in sensors, wireless networks, AI algorithms, and human-computer interaction.

A. RESEARCH GAP IN THE SLEEP MONITORING TECHNOLOGIES

For the in-home assessment tools, privacy-protected wireless tools and clinical reliability are the most important criteria that need to be taken care of. Video/image-based systems have issues with privacy, so systems based on raw data such as Wi-Fi-based, Li-Fi-based, or sensor-based should be selected. To guarantee clinical reliability, the systems should be standardized. The validation against gold standards (PSG or actigraphy) must be performed. Generalization of the sleep staging algorithm or learning model to consumer room layout is limited in such methods. Zhao et al. proposed such an approach using an adversarial training regimen to ensure the encoded features are influenced by user sleep physiology and not environmental variability [146].

The majority of the sleep systems focus on heart rate and breathing rate monitoring during sleep. However, brain monitoring is also very important to track EEG signals, especially for children and infants. Also, brain monitoring can potentially have therapeutic value through a neurofeedback sleep protocol as proposed by Hammer et al. [166]. Although there are commercially available brain monitoring devices
optimized for long-term comfort compared to traditional PSG like the Dreem Headset, they however, require extensive clinical trials to prove their viability and health benefits to consumers [167].

**B. RESEARCH SCOPE IN SLEEP MONITORING**

Beyond sleep disorders, there are other areas including neonatal, pediatric, gynecology and obstetrics, oncology, substance abuse, addiction, adolescent health, gerontology, and chronic disorders (e.g., diabetes, Alzheimer’s disease, arthritis, epilepsy, cystic fibrosis, Parkinson’s disease, etc.) that are potentially interesting venues for sleep technologies because these domains and conditions are known to be affected by poor sleep quality. Each domain or condition demands its own unique solution because no one sleep technology can solve their needs. For example, hallucinations and REM sleep behaviors are common issues in people with Parkinson’s disease [168]. Monitoring such sleep experiences require a new type of sensing and algorithmic modalities. Likewise, other domains have their unique constellation of sleep challenges that can be addressed through new sleep technologies, requiring interdisciplinary research and development.

The rise of affordable wearables (Dreem, Muse, Smart-Sleep Deep Sleep Headband, and Oura), including ones with PPG, ECG, EEG monitoring capabilities, enables in-home consumer-level multimodal sleep monitoring. The design of such wearables emphasizes user comfort for full night sleep monitoring. The longitudinal data obtained by such wearables and in-bed monitoring systems can allow for better monitoring of individuals with chronic sleep disorders and even by healthy individuals for better sleep wellness. This also creates an interesting interaction opportunity to utilize indoor environment factors such as ambient lighting, sound amplitude, and indoor air quality along with user activity and mobile device usage information to help users identify influences on sleep for long-term sleep wellness therapy. However, these new wearables demand for rigorous validation against gold standards before they can be applied in clinical interventions.

Learning algorithms are playing a cardinal role in sleep staging and demand significant efforts on expert scoring for ground truth. The increased volume of sleep physiological sensor records generated by wearables and in-home sleep sensing studies would be constrained by the availability of experts to evaluate the sleep signals. Further subjectivity in scoring between experts has been a notable concern, according to studies looking at an inter-rater agreement for sleep staging [169], [170]. While labs follow annotation protocol based on either R&K or AASM using full Sleep-Lab PSG, limited exploration has gone into how experts are to analyze data from diverse wearables, which provide different limited subsets of physiological sensing channels. Wearable ECG and ubiquitous optical heart rate sensors have made it feasible to use Heart Rate Variability metrics as a potential standard clinical metrics among wearables monitoring sleep. Physiological sensing data from wearables and/or actigraphy sensing data can be either provided directly to a deep learning model or the user-defined features extracted from input signals are provided to a machine-learning model to classify the sleep stage. The learning problem is frequently framed as a supervised learning problem using datasets of sleep signals with reference polysomnography scored by a sleep expert. The large repositories of public polysomnography sleep datasets provide an opportunity to study potential using unsupervised learning to learn sleep staging through clustering techniques.

**C. THE STANDARDS AND REGULATIONS ON SLEEP MONITORING TECHNOLOGIES**

Finally, yet importantly, there is a considerable amount of standards and regulations on sleep technologies. Sleep technology standards have a history of many years. The American Sleep Disorders Association (ASDA) (now known as the American Academy of Sleep Medicine-AASM) published standards of practice on the portable recording to assess OSA in 1994 [171]. In 2018, AASM published a position statement to define consumer sleep technology (CST) that includes apps, wearables, and patient-generated health data [172]. AASM set general principles of CST engagement and guidelines for clinicians encountering data from CST in a clinical setting. Khosla and her colleagues have raised concerns about the new sleep technology and their promises. In most cases, CSTs lack clinical validation and FDA clearance. Therefore, CSTs are not qualified to be used for making any diagnostic and/or treatment decisions. However, CSTs can be helpful in patient-clinician interaction in the context of sleep outcomes. It is recommended that CSTs demand rigorous validation in clinical sleep research with a promise of reproducibility that can be achieved through access to raw data and algorithms.

In a nutshell, we observe an upward trend in the adoption of consumer sleep technologies (CST). Although there are promising new sensing and algorithmic methods for sleep monitoring in daily life, there needs to be a lot more clinical research to measure the viability and health benefits of these new technologies. There is a strong demand for interdisciplinary research in sleep technologies. The inventors of sleep technologies need to work in close proximity with clinical sleep researchers who have a deeper understanding of sleep and its functions in healthy and clinical populations. It was often observed that new sleep technology is piloted on a handful of human participants with a minimum consideration of body types, gender, and age. The new sleep technologies will demand more rigorous testing on human participants. The recruitment of participants from minorities and ethnic groups is essential to increase the impact of sleep technologies beyond citizens from specific socioeconomic backgrounds. The studies that are aimed at monitoring sleep in naturalistic settings such as homes will demand user-centered approaches for robust deployments, data collection, and analysis. There is a constant tussle between the user’s comfort and accuracy in sleep research. In future studies, users need to be engaged and surveyed to measure their willingness to adopt the sleep technology.
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S. Khosla et al., “Consumer sleep technology: An American academy of sleep medicine position statement,” J. Clin. Sleep Med., vol. 14, no. 5, pp. 877–880, May 2018.
VIGNESH RAVICHANDRAN was born in Chennai, India, in 1995. He received the bachelor’s degree in electrical and electronics engineering from Anna University, in 2017, and the M.Sc. degree in electrical engineering from the University of Rhode Island, USA, in 2021, where he is currently pursuing the Ph.D. degree. His research interests include biomedical signal processing, biofeedback systems, the Internet of Things, and edge machine learning.

SHEHJAR SADHU (Student Member, IEEE) received the B.S. degree in computer science and data science from the University of Rhode Island, in 2020, where she is currently pursuing the M.S. degree in electrical engineering. She is also a Graduate Research Assistant at the University of Rhode Island. Her current research interests include app development and AI for wearable devices in the healthcare domain focusing on telehealth.

ALYSSA H. ZISK received the undergraduate degree in mathematics, mechanical engineering, and Mandarin Chinese, the master’s degree in mathematics from the University of Rhode Island, and the Ph.D. degree in interdisciplinary neuroscience from the University of Rhode Island, USA, in 2021. Her current research interests include communication and disability, including augmentative and alternative communication, and brain–computer interfaces.

AMY L. SALISBURY received the Ph.D. degree in developmental psychobiology from the University of Connecticut. She is a licensed nurse practitioner in child and family psychiatry. She is a Ph.D., LNP, PMH-CNS, BC, FAAN, a Professor, an Associate Dean for Research, Scholarship, and Innovation at the School of Nursing and the Director of Research at the Institute for Women’s Health, Virginia Commonwealth University, Richmond, VA, USA.

She has expertise in measurement and assessment of fetal and infant neurobehavior and sleep development. Her research interests include longitudinal research examining the impact of prenatal exposures, maternal psychiatric conditions, and their treatments on neurodevelopmental outcomes.

DHAVAL SOLANKI (Member, IEEE) received the Ph.D. degree in electrical engineering from the Indian Institute of Technology Gandhinagar, India, in 2020.

He is currently acting as the Co-Director at the Wearable Biosensing Laboratory, University of Rhode Island, USA. He also serves as a Lecturer at the Department of Electrical, Computer and Biomedical Engineering, University of Rhode Island. From 2021 to 2022, he served as a Postdoctoral Research Scholar at the Wearable Biosensing Laboratory. His current research interests include wearable device, biosignal processing, virtual reality, and assistive and physiology-sensitive systems for neuro-rehabilitation.

KUNAL MANKODIYA (Member, IEEE) received the B.E. degree in biomedical engineering from Saurashtra University, India, in 2003, and the M.S. degree in biomedical engineering and the Ph.D. degree in computer science from the University of Luebeck, Germany, in 2007 and 2010, respectively.

From 2011 to 2014, he was a Postdoctoral Researcher at the Intel Science and Technology Center (ISTC) affiliated with Carnegie Mellon University (CMU), Pittsburgh, PA, USA. He is currently an Associate Professor of biomedical engineering and the Director at the Wearable Biosensing Laboratory, Department of Electrical, Computer, and Biomedical Engineering, University of Rhode Island, RI, USA. In 2012, he published a book on wearable health monitoring that serves as a hands-on guide to program high-end application processors for healthcare applications.

Dr. Mankodiya is a member of ACM and Biomedical Engineering Society and serves in the professional society in various capacities. He was a recipient of the TechConnect Defense Innovation Award, in 2018, the NSF CAREER Award, in 2017, the Innovator-of-the-year Future Textiles Award-Germany, in 2017, the 40 under 40 Providence Business News Award, in 2017, the NSF CRII Award, in 2016, and the 2010 SYSTEX Award-Belgium, in 2010. He regularly organizes scientific workshops/symposiums on the Internet of Things (IoT) and wearable systems for healthcare at various international conferences.