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Perspective—Longitudinal Sleep Monitoring for All: Payoffs, Challenges and Outlook

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Longitudinal tracking of sleep metrics is important for detecting and managing various diseases, spanning cardiorespiratory disorders to dementia. However, at present, sleep monitoring primarily occurs in specialized medical facilities that are not conducive to long-term studies. In-home solutions either compromise user comfort or signal accuracy in tracking sleep variables and have not yet provided reliable longitudinal data. Here, we survey the current state of sleep trackers and highlight key shortcomings to provide guiding principles for improved sensor system design. We believe that human-centered design of multimodal, low-form-factor, comfortable sensing systems is needed for this increasingly-important area of human health monitoring.
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There is growing commercial, clinical and academic interest in sleep monitoring because of mounting evidence that links sleep disruptions and sudden changes in sleep patterns to diminished cognitive function, diabetes, high blood pressure, heart disease, obesity, and depression.[1–6] There is also growing interest in improving detection of sleep disorders, which affects 50 to 70 million Americans of all ages and socioeconomic classes.[7] Further, recent work has shown that sleep monitoring has potential as a marker for Alzheimer's disease pathology. Longitudinal changes in cognitive function have been correlated with consistent changes in selected sleep metrics and evidence also suggests that sleep disturbance itself can contribute to cognitive decline and heighten the risk of Alzheimer's disease by increasing β-amyloid burden.[8–10] Sleep disturbances also often precede (by up to years) the diagnosis of Alzheimer's disease and may even appear before onset of cognitive decline.[11] There exists, therefore, a significant need for comfortable sleep monitoring solutions that can be used regularly (e.g., at least once a week for three-six months) by non-specialist users to measure sleep metrics at home and thereby detect changes in sleep behavior and quality.

Traditional sleep monitoring tends to mainly focus on sleep macrostructure, i.e., classifying sleep stages and quantifying the amount of time spent in each sleep stage relative to total sleep time (TST). Sleep stages include: wake; rapid eye movement (REM) sleep; light sleep (Stage 1, or non-REM N1); intermediate sleep (Stage 2, or non-REM N2); and deep sleep (Stage 3, slow wave sleep, or non-REM N3).[12] Of particular note is the slow-wave or deep sleep phase—this phase constitutes the deepest, most refreshing and physiologically-restorative sleep type, which tends to diminish in duration with age.

Table I summarizes the biosignals that are used to classify sleep stages and gain a holistic understanding of sleep. Electroencephalography (EEG), is considered the most important signal for high-quality sleep monitoring.[12] Indeed, each sleep stage is actually defined based on a characteristic EEG pattern—each sleep stage is characterized by brain waves of specific frequencies and/or amplitudes. However, since some sleep stages are also associated with certain types of eye movements and muscle activities, electrooculography (EOG) and electromyography (EMG) measurements are also recorded in tandem to confirm or disambiguate sleep stage classifications. Cardio-respiratory parameters are particularly useful for understanding sleep disorders, such as apnea. In addition, gross body movements during sleep, such as periodic leg movements, are important when studying somnambulism or monitoring the sleep behavior of older, cognitively-impaired adults in care facilities. Thus, in addition to EEG and EOG, measurements of cardiorespiratory features, body temperature and muscle activity are also included in laboratory-based polysomnography (PSG) systems, which are considered the most clinically accurate method of monitoring sleep.

In addition, microstructural EEG features during sleep are emerging as clinically important tools for diagnosing cognitive disfunctions and age-related decline. Shorter timescale phasic EEG events, such as k-complexes, spindles and delta wave bursts,[13,14] are not widely used for standard sleep stage scoring; however, research has shown that aging-related changes are particularly reflected in fast spindle density, k-complex density, and delta power during intermediate sleep.[15] Further, diminishing time in slow-wave or deep sleep with age has been shown to increase the concentration of β-amyloids in the brain,[10] which heightens the risk of developing dementia. Therefore, as our understanding of sleep parameters and their correlations to mental and physical disorders evolves, it is also becoming more and more important to have access to raw signals from various sleep tracking systems to provide a richer data set on which accurate clinical diagnoses and early interventions can be based.

Current Status

Contemporary work on sleep trackers can be classified into four categories based on the form factor of the device: (1) non-wearable sleep trackers, which includes mattress- or bedding-embedded systems and room-integrated systems, (2) wrist-worn sleep trackers, (3) head-worn sleep trackers, and (4) garment or fabric-integrated sleep trackers. Table II summarizes the biosignals recorded by these categories of in-home sleep monitoring systems and compares them to the clinical gold-standard, the laboratory-based polysomnography (PSG) system.

Non-wearable sleep trackers.—There are a number of efforts that propose to instrument the environment around the user, for example inside a mattress or bedding, or in the room containing the mattress. Accelerometers and/or piezoelectric units, and thermistors have been embedded into mattresses and bedding to measure heartbeats, heart rate, respiration, gross body movements and body

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Table I. Representative biosignals used to classify sleep stages. A check mark denotes that strong, high intensity biosignals are generated, whereas a cross mark means that little to no signal can be observed.

Sleep Stage	Brain Activity (EEG)	Eye Movement (EOG)	Gross Body Movements (EMG)	Heart Rate	Respiration
Wake	✓ (Irregular)	✓ (Irregular)	✓ (Irregular)	Irregular	Irregular
Rapid Eye Movement (REM)	✓ (Beta, 12–32 Hz)	✓ (fast rapid movements)	✗ (paralysis)	Fast, Irregular	Fast, Irregular
Light Sleep (Stage 1, non-Rem N1)	✓ (Theta, 4–8 Hz)	✓ (slow cyclic eye rolling)	✓ (Occasional Twitches)	Slow, Regular	Slow, Regular
Intermediate Sleep (Stage 2, non-REM N2)	✓ (Theta, 4–8 Hz, spindles and k-complexes)	✗ (minimal)	✗ (minimal)	Slow, Regular	Slow, Regular
Deep Sleep or Slow-Wave Sleep (Stage 2, non-REM N3)	✓ (Delta, 0.5–4 Hz)	✗ (minimal)	✗ (minimal)	Lowest, Regular	Lowest, Regular

Table II. Summary of biosignals recorded by currently-known sleep monitoring systems. A combined check/cross mark indicates that only selected models record a certain biosignal.

	Brain Activity	Eye Movement	Gross Body Movements	Body Temperature	Blood Oxygen Level	Heart Rate/Blood Pulse Wave
Clinical-Grade Polysomnograph	✓	✓	✓	✓	✓	✓
Mattress- or Bedding-Embedded Trackers	✗	✗	✓	✗✓	✗	✓
Room-Integrated Trackers	✗	✗	✓	✗	✗✓	✓
Wrist- or Finger-Worn Trackers	✗	✗	✓	✗✓	✗✓	✓
Head-Worn Trackers	✓	✓	✗	✗✓	✗✓	✓
Garment- or Fabric-Integrated Trackers	✗✓	✗✓	✓	✗		✓

temperature (e.g., Murata, Beddit). There are also examples of installing cameras or radar systems in the room containing the mattress to find selected physiological variables (respiration, heart rate and/or blood oxygen level) and track head posture and body movement during sleep.[16,17]

While all these non-contact sleep tracking solutions have the advantage of being unobtrusive and, therefore, useful for longterm studies, they tend to be imprecise and noisy. The imprecision stems from the inability to observe the most valuable signal for sleep monitoring—EEG—and relying on chest movements during respiration and gross body movements to infer sleep markers.[18] Further, the signals from all of these non-contact sensing systems are confounded by proximate activity by bed partners or caregivers and other moving objects in the vicinity, like a fan.[19]

Wrist- and finger-worn sleep trackers.—Wrist- or finger-worn devices are, at present, the most pervasive and commercially-accessible devices for in-home sleep tracking. All of these devices use hard electronic components, such as light-emitting (laser) diodes, cameras/photodetectors and inertial measurement units (IMUs), to measure blood pulse waves and body movement from the wrist or fingers (e.g. Fitbit, Garmin, Actiwatch, Whoop, and Oura Ring). Certain models also contain dry, metal electrodes to measure cardiac parameters and/or skin temperature, and others quantify blood oxygenation levels.

Due to intense, broad-reaching commercialization efforts, these wrist- and finger-worn devices are the most aesthetically-advanced sleep tracking solutions, with imperceptibly integrated electronics and wireless communication components. Through a combination of hardware engineering and clever data sampling/transmission strategies, these devices have, to date, been designed to function for at least eight hours before requiring a battery recharge. The main disadvantage of these solutions is the inability to directly monitor EEG and EOG signals, which are the only signals that allow accurate sleep stage classification (EEG), meaningful sleep quality analysis (EEG+EOG) and clinical diagnosis of cognitive decline and mental disorders (EEG). At present, all wrist- and finger-worn sleep trackers simply infer sleep stage based solely on cardiac, respiratory and gross body movement information, which results in poor accuracy and precision in sleep scoring.

Several studies have been conducted to validate these wrist- and finger-worn sleep trackers in comparison to the gold-standard, laboratory-based PSG systems.[20–23] On average, across multiple models of these actigraphy-based trackers, sleep stages could only be identified/classified with approximately 60% accuracy for a large population of healthy adults.[24] No validation dataset is available, to the best of our knowledge, for older populations and those at risk for cognitive decline.

Head-worn sleep trackers.—Head-worn solutions hold more promise for meaningful sleep tracking as they allow recording of sleep-relevant biopotential signals from the head (EEG and EOG), as compared to wrist- or finger-worn devices that cannot reveal the same information. The Phillips Smartsleep headband uses adhesive-backed disposable electrodes placed behind the ear to obtain EEG signals during sleep. Despite the high signal quality of these electrodes, they are uncomfortable due to the adhesive and are not practical for long-term wear, since, once the gel dehydrates, the electrode loses its functionality and needs to be replaced. Further, these electrodes and the headband itself cannot be sanitized or laundered, which creates a hurdle for consistent longterm use.

Dry electrodes are comparatively more prevalent in head-worn sleep trackers. Commercially available headbands such as Muse, Dreem, Brainbit, Neuroon, and SleepProfiler, use dry metal electrodes to obtain EEG from the forehead. Some devices also have an optical photoplethysmography (PPG) sensor for cardiac and respiration rate tracking and/or extra dry electrodes for EOG. In-ear sensors to record EEG have also gained interest,[25,26] as well as a temporary-tattoo dry electrode placed on the head[27] for capturing EEG, EOG, and EMG during sleep.

The main drawbacks of most head-worn systems are the rigid scaffolding of the device and the use of either hard or adhesive-based sensing components that touch the skin on sensation-rich areas. These features can make the system highly uncomfortable in different sleep postures and are not ideal for continuous long-term sleep tracking. For devices placed on the head, weight, feel and form factor play an outsized role in use frequency and perceptions of comfort, especially for older adults. Further, users with sensitive or compromised skin are loathe to use adhesive- or tattoo-based devices during sleep. Another debatable aspect of the current head-worn solutions is the quality of the acquired biopotential signals—the majority of these technologies use dry electrodes to avoid adhesives and enable sanitization protocols, however, this results in a considerable increase in motion artifacts.[28]

Garment- or fabric-integrated sleep trackers.—Physiological, biopotential and physical sensing through fabric-based elements has gained interest during the past decades, particularly in the academic research realm. Many of these devices are based on conductive fabric- or fiber-based dry electrodes sewn or knitted/woven into tight-fitting clothing to measure various physiological parameters,[29] including cardiac, respiration, and activity information. There have also been some studies on the design of textile-based dry electrodes that can be integrated into rigid head-worn devices to extract certain biopotential signals, similar to the commercial head-worn devices described earlier.[30]

The basic problem with many fabric-based prototypes is that dry electrodes are inherently susceptible to noise and, when incorporated into garments, fabric-based dry electrodes are further subject to motion artifacts and static-field couplings to the body, which, together, severely compromise the signal-to-noise ratio (SNR) and reliability of these prototypes. Further, fabric- and garment-integrated sensing systems shoulder the added burden of needing to be mechanically-rugged, launderable/wash-stable and recoverable—features that many research reports do not thoroughly and reliably evaluate prior to publication.

Nonetheless, selected research groups are currently endeavoring to produce launderable, comfortable garments containing a distributed network of fabric-based sensors that reveal key metrics relevant to sleep. Most notable among these efforts are: (1) a loose-fitting pajama shirt[31] that uses fabric-based piezoionic pressure sensors[32] to extract cardiac and respiration features, in addition to sleep posture, during sleep, (2) a foam/fabric eye mask outfitted with recoverable and launderable wet-hydrogel electrodes for EOG,[33] and (3) a soft/adjustable fabric head wrap that captures clinically-accurate EEG, in addition to physiological and physical signals (cardiac, respiration, general body movement, and head posture), through fabric-based sensors on the head.[34] Although these highlighted examples are lab prototypes that require broader independent validation, they boast a combination of heretofore unmatched features (launderability, comfort, signal accuracy) that hold great promise for consistent, longitudinal in-home sleep tracking by non-specialist users.

Future Needs and Prospects

Our understanding of sleep and its effects on human health are constantly evolving, as is the clinical understanding of relevant sleep markers for diagnosing various pathologies. What is clear, however, is that in-home monitoring of sleep behavior and sleep quality over long periods of time allows users with diverse backgrounds and pre-existing conditions to better manage their own health and aging, and pursue early interventions as needed.

However, achieving high-quality in-home sleep monitoring is complicated by the number of sensor modalities and locations that need to be simultaneously sampled to provide an accurate and holistic picture of sleep. Diverse sensors and discrete electronic components need to be placed on the head, as well as several other locations on the body to provide a complete suite of measures that accurately reveal sleep macro- and microstructure.

While commercially-available wrist- or finger-worn "sleep trackers" are comfortable, they sacrifice fidelity and precision. At present, in-home sleep sensing devices actually rely on surrogate measures of sleep, such as heart rate, breathing, and body movement signals, rather than EEG, which is the only measurable determinant of sleep stages. Since the surrogate signals only capture a coarse temporal structure of sleep, they provide only coarse-level sleep metrics, like total sleep time and percent REM sleep, and, in some cases, macro-structural analysis of sleep such as sleep stages. In addition, metrics provided by these devices are only accurate for "normal" healthy adults and not individuals with sleep disorders or other cognitive maladies. This is because these devices need to compensate for the imprecision of surrogate measures by relying on large population-level data analysis but these measures are erroneous for individuals whose sleep patterns do not follow population averages. For example, the REM sleep stage is known as a state where a person experiences random/rapid movement of the eyes, accompanied by low muscle tone throughout the body, and the tendency to dream vividly. However, a person who is suffering from a sleep disorder or dementia usually has violent arm and leg movements during the REM sleep stage. Sleep monitors that use surrogate measures of sleep assume that the body normally freezes and does not move during REM since they solely measure the cardio-respiratory features and gross body movement—this means that such sleep monitors will erroneously classify the REM sleep stage in a person suffering from sleep disorders or dementia as a "wake" stage, or possibly a "light sleep N1" stage, thus providing a misleading picture of sleep quality. As a result, these sleep trackers are inaccurate for individuals with substantial clinical needs and medication-induced sleep disruptions. Similarly, for the same reasons, sleep monitors that use surrogate measures of sleep also often erroneously classify a "wake" period as a REM sleep or deep sleep N2 stage in healthy adults, particularly if a user remains very still for long periods of time, for example, while reading. They also fail to capture day/night (circadian) rhythm sleep patterns of individuals with sleep abnormalities (such as older adults with dementia).

Other sleep trackers focus on accuracy and, therefore, perform EEG but sacrifice some modicum of comfort, adaptability or user-friendliness in the process. Most of the head-worn sleep trackers that have advanced to validation studies and/or the commercial market require rigid sensing elements that are pressed tight against the head or held directly on the skin. For example, the Phillips Smart Sleep headband uses behind-the-ear sticker electrodes, the Muse and SleepProfiler have an optical sensor on the forehead and EEG electrodes inside a rigid box/frame, and the Dreem has bone conduction electrodes that need to be held tightly against the user's head. Such rigid scaffolds and the embedded hard components make these devices uncomfortable to wear during sleep and, therefore, these sleep trackers are not consistently used over long periods of time to track meaningful changes in sleep behavior and sleep quality.

Another important limitation of head-worn trackers is that, despite performing EEG, most devices do not currently have adequate SNR to expose microstructures of sleep, such as spindles and k-complexes, with the singular exception of the SleepProfiler. This is a missed opportunity since these sleep microstructures play an essential role in information processing and long-term memory consolidation, and are biomarkers of both Alzheimer's disease pathology and seizures. As compared to the gold-standard laboratory PSG systems, most head-worn trackers suffer from poor SNR in their EEG signals, because the dry electrodes used in these trackers are inherently noisy to start and are subsequently further confounded by motion artifacts, dirty skin conditions and/or the presence of hair on the skin, and suboptimal electrode placement when the device is not placed on the head correctly (or does not fit perfectly on a user's head). Fabric-based sleep trackers containing wet hydrogel electrodes deftly overcome these SNR issues while also being comfortable to wear, though these devices still need to be transitioned from the lab to the commercial market.

As our understanding of sleep parameters and their correlations to mental and physical disorders evolves, it is also becoming more and more important to have access to raw signals from various sleep tracking systems to provide a richer data set on which accurate clinical diagnoses and early interventions can be based. However, data analytics cannot be performed using many commercial sleep tracking solutions due to proprietary issues or lack of availability of raw sensor data, which makes ground-truthing and independent validation challenging or impossible. Therefore, ideally, all in-home sleep monitoring solutions should be graded against a set of robust and standardized validation parameters to ensure, at minimum, proper sleep scoring in diverse populations with various pre-existing conditions and medication regimens.

Summary

Gaining a holistic understanding of sleep metrics is increasingly important for human health management. However, sleep is a challenging context in which to perform reliable, longitudinal sensing because of the diverse suite of biosignals that need to be extracted from different locations on the body while honoring the user's heightened need for comfort during sleep. Further, for early diagnosis of certain pathologies, consistent and clinically-accurate measurement of brain activity (EEG) is necessary, as opposed to stochastic and disjointed monitoring of surrogate measures (such as cardiorespiratory features and gross body movements).

Despite living through an exciting, golden age of sensors,[35] robust solutions for reliably tracking sleep measures in-home remain elusive. Innovative, human-centered design of multimodal, low-form-factor, comfortable, reusable sensing systems for sleep monitoring needs to be pursued, along with robust independent validation of any lab prototypes across diverse populations. Ample room exists for improved materials and electrode engineering to access comfortable skin-contact based biopotential electrodes that are recoverable, resist fouling during long-term use and produce high SNRs. Creative methods for integrating and/or embedding sensors into garments and accessories will greatly ameliorate user adoption and increase consistent use. Lastly, earnest ground-truthing efforts and real-world validation with diverse (in age, gender, pre-existing conditions and risk states) populations are integral for identifying strong sensing solutions for sleep monitoring.

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