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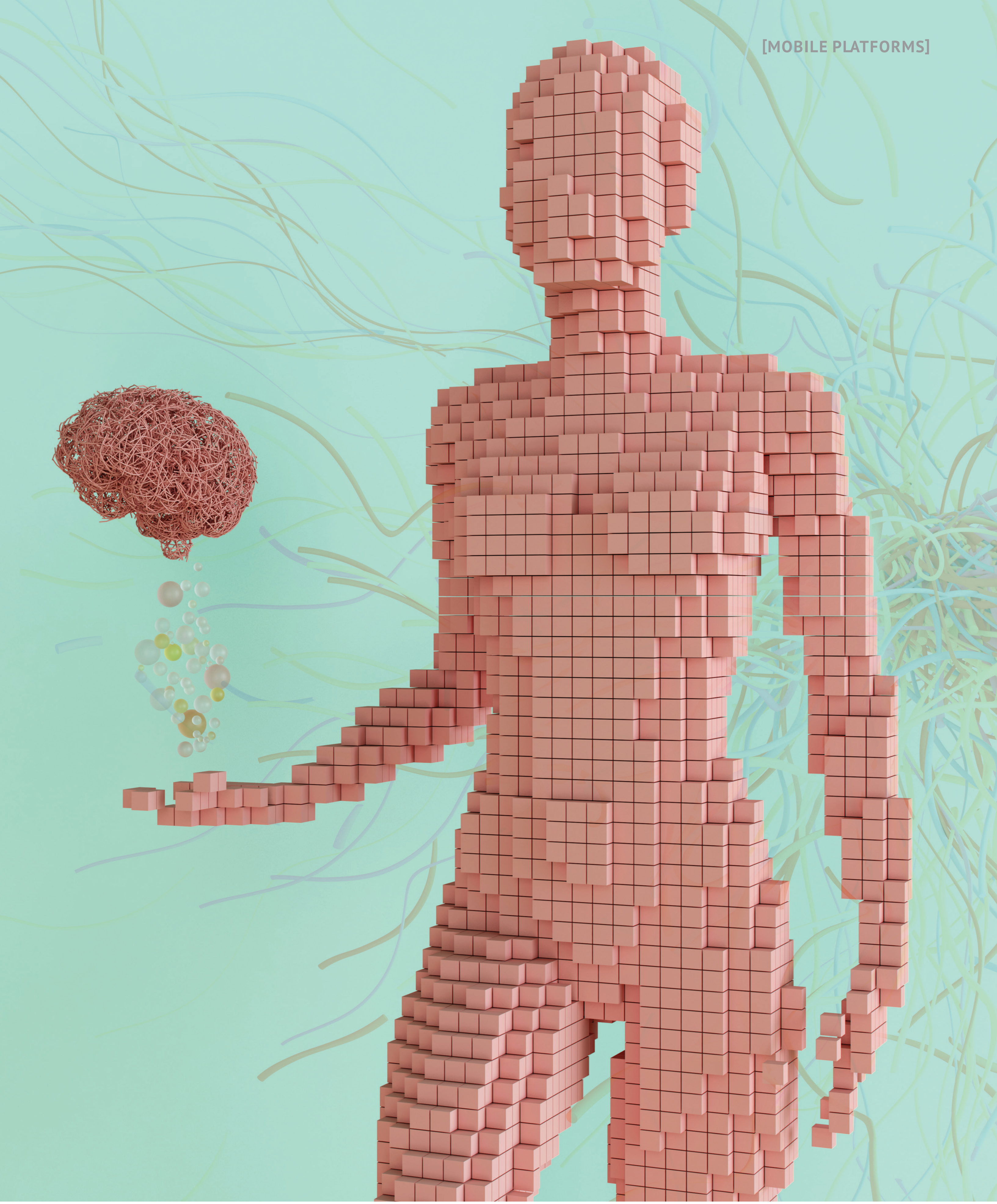
MOBILE SENSING OF ALERTNESS, SLEEP, AND CIRCADIAN RHYTHM: Hardware & Software Platforms

Human biology is deeply rooted in the daily 24-hour temporal period. Our biochemistry varies significantly and idiosyncratically over the course of a day. Staying out of sync with one's circadian rhythm can lead to many complications over time, including a higher likelihood for cardiovascular disease, cancer, obesity, and mental health problems [1]. Constant changes in daily rhythm due to shift work has been shown to increase risk factors for cancer, obesity, and Type 2 diabetes. Moreover, the advent of technology and the resultant always-on ethos can cause rhythm disruption on personal and societal levels for about 70% of the population [2].

Circadian disruption can also cause a serious deficit in cognitive performance. In particular, alertness – a key biological process underlying our cognitive performance – reflects circadian rhythms [3]. Sleep deprivation and circadian disruption can result in poor alertness and reaction time [3]. The decline in cognitive performance after 20 to 25 hours of wakefulness is equivalent to a Blood Alcohol Concentration (BAC) of 0.10% [4]. To compare, in New York State, a BAC of more than 0.05% is considered "impaired" and 0.08% is considered "intoxicated" [5]. In other words, the effects of sustained sleep deprivation and circadian disruption on cognitive performance is similar (or worse) to being intoxicated.



Sleep and circadian issues also result in serious productivity loss and work occupational accidents in the workplace. The yearly economic loss caused by insufficient sleep amounts to a staggering $411 billion in the USA alone [6]. The incremental cost to employers from productivity loss, absenteeism, turnover, workplace accidents, and increased insurance and medical costs are more than $10,000 per year per shift worker over and above the cost of a comparable day worker [7], [8]. Sleep and circadian disruption also adversely impact memory and learning capabilities. In particular, hippocampal-dependent learning and memory forming strongly reflects circadian influence [9].

Overview: The central circadian clock for humans is located in the suprachiasmatic nucleus (SCN) of the hypothalamus [36] (Figure 1) and drives circadian rhythmicity in other brain areas and peripheral tissues by sending them neural and humoral signals. Environmental periodical cues can reset the phase of the central pacemaker so that the period and phase of circadian rhythms coincide with the timing of the external cues. Most peripheral tissues and organs contain circadian oscillators. Usually, they are under the control of the SCN; however, under some circumstances (e.g., restricted feeding, jet lag and shift work), they can desynchronize from the SCN. Central pacemakers and peripheral oscillators are responsible for the daily rhythmicity observed in most physiological and behavioral functions, such as sleep-wake cycles, physical exercise, and feeding time, providing feedback in turn that can modify the function of the SCN and peripheral oscillators.

Since SCN is located deep in the brain, it is not feasible or ethical to measure the status directly. Traditionally, human circadian phase is evaluated by a 26-50h inpatient assessment of continuous core body temperature or multiple hours of blood or saliva samples for melatonin assay [10]. Such assessments are invasive, time consuming, and resource intensive.

In recent years, mobile sensing researchers have been exploring ways to unobtrusively and passively infer one's circadian rhythm and link the measure to her cognitive ability, performance, sleep and well-being. These mobile sensing technologies have enabled individuals to monitor their daily lives and enabled scientific investigators to passively

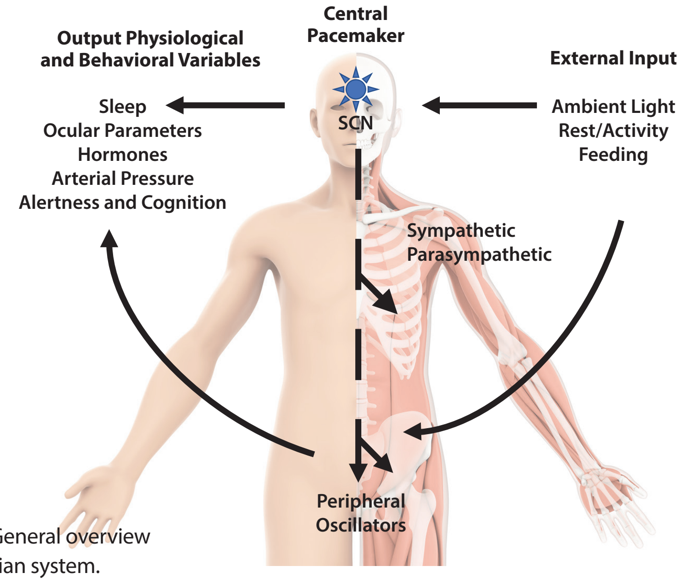
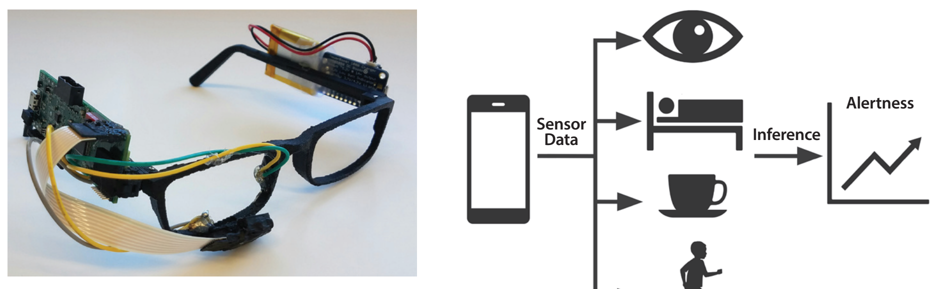


FIGURE 1. General overview of the circadian system.



(a) iShadow

(b) Alertness Scanner

FIGURE 2. Hardware and Software Platforms for Alertness Sensing.

collect real-time data without disrupting people's habitual routines. Multiple time-points of less invasive wearable or mobile activity or physiological sensors have been applied to infer circadian rhythm and alertness [11]–[14].

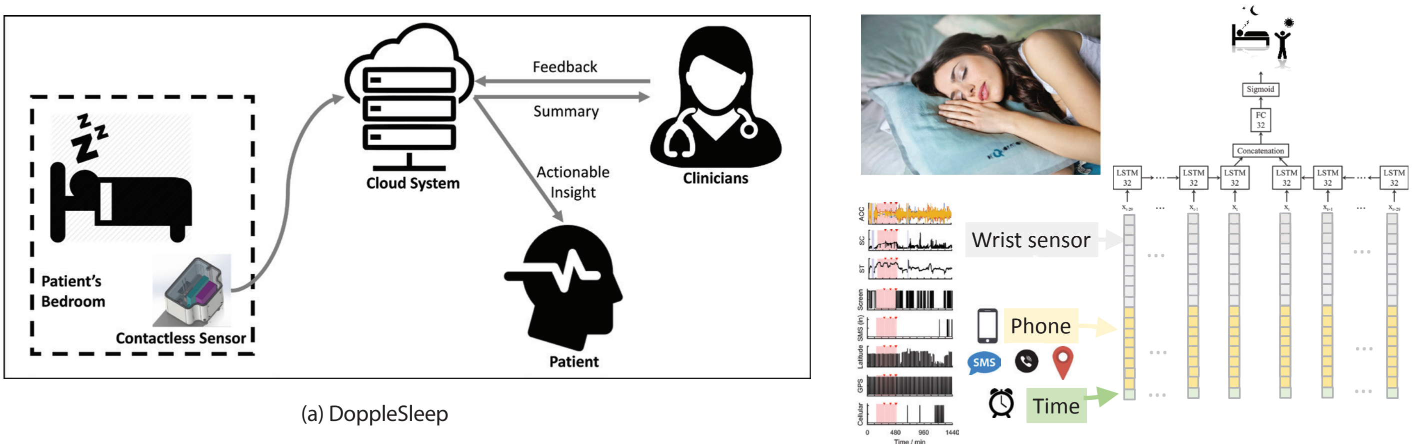
In this article, we will discuss some of the key technical challenges associated with designing such mobile sensing technologies from both the hardware and software point of view. We will highlight some of the most recent and promising hardware and software platforms for mobile sensing of alertness, sleep, and circadian rhythm. Finally, we will discuss future opportunities in this research direction.

TECHNICAL CHALLENGES

There are a number of technical challenges associated with designing mobile sensing technologies for capturing alertness, sleep, and circadian rhythm information in an unobtrusive manner.

a) **Balancing Accuracy-Obtrusiveness** How to unobtrusively measure internal physiology and behavior to accurately infer about sleep, alertness and circadian rhythm is one of the most important design considerations. More specifically, balancing accuracy and obtrusiveness of the mobile sensing technology is the key for the scalability and potential real world impact. Technologies and procedures that are invasive and intrusive tend to capture the internal physiological factors more accurately.

b) **Robustness** The second key challenge is variability across environments. The sensing modules can be deployed in relatively static environments like the bedside to moderately dynamic environments like the workplace to highly dynamic environments such as a vehicle. As a result, methods/techniques to handle diverse and dynamic environments are warranted.



(a) DoppleSleep

(b) LSTMSleep

FIGURE 3. Hardware and software platforms for sleep sensing.

c) **Performance** The third key challenge is to design and implement a hardware software design that can achieve privacy and energy efficiency. To ensure privacy, we need to process the raw sensor streams locally without uploading to the cloud. This requires an efficient computation fabric that can compute markers locally on the sensing modules.

HARDWARE AND SOFTWARE PLATFORMS FOR ALERTNESS, SLEEP, AND CIRCADIAN RHYTHM SENSING

Alertness Sensing

iShadow: iShadow (Figure 2a) [21], [22] is a novel near-infrared spectroscopy (NIR) imaging based ultra-low power wearable eyeglass platform for fatigue and alertness sensing. This work uses sparse sampling together with NIR imaging to achieve high frame rates at milliwatts power consumption. It measures gaze direction, pupil dilation, blink rate, saccadic movements, and other eye-related parameters from which cognitive measures, such as fatigue and alertness can be extracted. Some of the major capabilities of our system includes: (1) we provide a sparse neural network-based approach that enables gaze tracking at low power [21], (2) we track pupil size and pupil position by leveraging adaptive sampling approaches [23], (3) we show in [22], a system that estimates eyelid location and blinks at low power and enables us to infer cognitive state such as drowsiness and fatigue. Collectively, our approaches allow us to operate at high frame rates of 100-250 fps, while consuming only a few tens of milliwatts of power and requiring only a micro-controller with a few tens of kilobytes of memory for processing.

AlertnessScanner: AlertnessScanner (Figure 2b) [24] is a mobile application for Android smartphones that can infer alertness by leveraging front-facing pictures taken passively from smartphones, such as during screen unlocks. Measuring reaction time from the Psychomotor Vigilance Task test at different times in a day as ground truth of alertness is relatively highly intrusive and requires active participation from the user. This system predicts alertness by extracting the pupil to iris ratio from pictures of the user's face and using a regression model. Based on results from two in-the-wild studies, it was found that AlertnessScanner can infer alertness without requiring any action from the user beyond the normal smartphone usage.

Sleep Sensing

DoppleSleep: Radar-based sleep sensing is a new promising technology for contactless measurement of sleep quantity and quality. Radar modules can be manufactured in the form of relatively small BiCMOS chips, suitable for integration in portable electronic devices. Radio frequency signals have been interpreted with convolution and recurrent neural networks for sleep stage prediction to fairly accurately predict sleep in healthy young people [17]. There has even been some early work with radar to detect sleep apnea [18, 19].

WE DISCUSS TECHNICAL CHALLENGES ASSOCIATED WITH DESIGNING SUCH MOBILE SENSING TECHNOLOGIES

DoppleSleep is such a contactless sleep sensing platform, using a 24 GHz Doppler radar for estimating sleep stages [20]. By estimating the Doppler frequency shift in the backscattered wave from an individual's body, it tracks the person's body movement, including turning, moving limbs, and sitting. As human body motion is different from that of machine motion in the frequency domain, DoppleSleep can also filter out extraneous motion from various machines and appliances (e.g., fans, air conditioning units, or speakers) in the room. As heart and breathing rate falls in different parts of the frequency spectrum, they could be separated with frequency-based technique.

DoppleSleep (Figure 3a) fuses body motion, heart rate, and breathing rate information to model sleep stages and quality in a single person-sleeping scenario. Overall, with a Leave-One-Subject-Out (LOSO) cross-validation experiment, DoppleSleep achieved an F1 score of 89.1% for sleep versus wake classification and an F1 score of 80.2% for REM versus Non-REM sleep stage

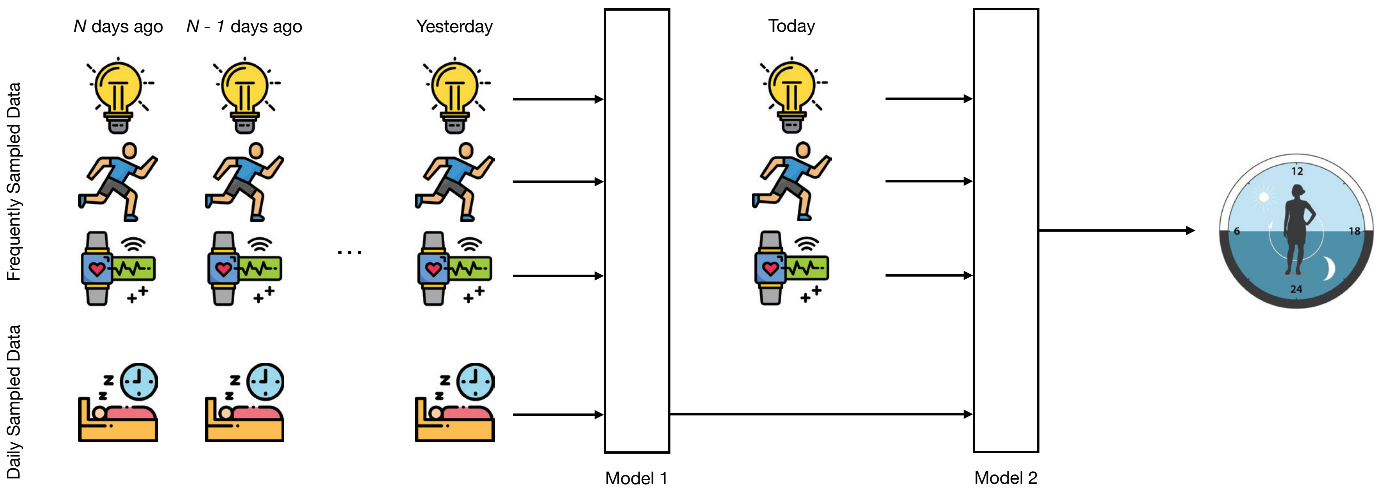


FIGURE 4. BiTimescale: Two-Step framework for estimating dim light melatonin onset.

classification for eight participants in their homes. More importantly, such a radar-based platform can also be effective at finding the root physiological condition or cause of different sleep and circadian disruptions, and in suggesting actionable recommendations with the help of advanced AI techniques and a clinician in the loop.

LSTMSleep: Machine learning and statistical models have been developed for ambulatory sleep detection from continuous smartphone and wearable sensor data [11-14], [26], [25], [28-32]. Recently, a type of recurrent neural network with long-short-term memory (LSTM) cells for synthesizing temporal information was used to develop an algorithm that uses multimodal data (e.g., location, inertial sensor, app usage, text and phone call log) from smartphones and wearable technologies to detect sleep/wake state and sleep onset/offset (Figure 3b) [28]. The model was trained based on 5580 days of multimodal data from 186 participants and compared the new method for sleep/wake classification and sleep onset/offset detection to (1) non-temporal machine learning methods and (2) a state-of-the-art actigraphy software. The new LSTM method achieved a sleep/wake classification accuracy of 96.5%, and sleep onset/offset detection F1 scores of 0.86 and 0.84 respectively, with mean absolute errors of 5.0 and 5.5 min, respectively, when compared with sleep/wake state and sleep onset/offset assessed using actigraphy and sleep diaries. The LSTM results were statistically superior to those from non-temporal machine learning algorithms and the actigraphy software. The new algorithm showed good generalization by comparing participant-dependent and participant-independent models and making the model nearly real-time with slightly reduced performance.

Circadian Rhythm Sensing

Multiple human circadian phase markers, including melatonin, core body temperature (CBT), and cortisol have been used for research and clinical purposes [15].
A substantial number of studies have demonstrated that the onset of melatonin secretion under dim light conditions (also called Dim Light Melatonin Onset, or DLMO in short) is the single most accurate marker for measuring the circadian phase information [33]. The secretion of melatonin is regulated by various factors, including the circadian clock, lighting conditions, mood, and exercise [37]. Under dim light conditions in normally entrained humans, the secretion of melatonin remains at a low level during the daytime and increases sharply for about two hours prior to habitual bedtime [38]. Monitoring melatonin profiles, however, requires frequent collection of saliva or blood over at least seven hours in dim light conditions; this is expensive and inconvenient and, since these samples must be sent for assay, results are not available immediately. As a result, innovations in sensing are required that will be both accurate and unobtrusive.

There is some ongoing work to estimate DLMO using machine learning or statistical regression models and unobtrusive sensor data, such as sleep-wake patterns, skin temperature, heart rate and light exposure [11–13]. Some studies investigated the relationships among sleep regularity, circadian disruption and performance and wellbeing [25], [27] [34]. Most studies leverage either daily sampled data (sleep onset/offset time) [40, 41] or frequently sampled data (including light exposure, skin temperature, activity every minute) [42–44]. In our recent work, BiTimescale, we propose a two-step framework for estimating DLMO using the data of both time scales (Figure 4) [45]. The first step summarizes the data prior to the current day, while the second step combines this summary with frequently sampled data of the current day. We evaluate several variants of a moving average model, which inputs sleep timing data as the first step and recurrent neural network models as the second step for estimating DLMO. The experimental results show that our two-step model with two-time-scale features has statistically significantly lower root-mean-square errors than the models that use either daily sampled data or frequently sampled data alone.

FUTURE OPPORTUNITIES

Looking ahead, despite these initial hardware and software successes in sensing circadian rhythm and its related biomarkers (e.g., alertness, sleep), there are still gaps and barriers in the circadian phase and misalignment modeling. One major challenge in circadian rhythm sensing is that it is hard to measure pure circadian rhythm in daily life settings because environmental and behavioral factors could mask the pure internal rhythm [39]. Another major challenge in circadian phase estimation is that the circadian process is coupled with homeostatic rhythm and disentangling the circadian process from the homeostatic process is challenging [16]. Further exploration in multimodal modeling of these circadian and homeostatic processes in a multitask approach might be a promising new direction to explore. Another underexplored direction is developing a feedback-loop system, in which circadian rhythm sensing would be coupled with intervention. For example, a circadian rhythm-aware alertness model of a shift worker (e.g., firefighter) that can predict when her alertness level will be below a certain threshold can trigger an intervention (e.g., an SMS encouraging a break/nap/cup of coffee). In the future, we hope to connect ubiquitous sensing and modeling technologies to interventions to develop a closed-loop system for enhancing cognitive ability and well-being (Figure 5). ■

FIGURE 5. Intelligent Cognitive Assistant using ubiquitous sensing, modeling and interventions.

Akane Sano is an assistant professor at Rice University. Her research focuses on human sensing, modeling, and interventions for health, well being, and performance. She completed her PhD at MIT on designing methodologies and tools to collect and analyze wearable and mobile sensor data for measuring and improving stress, mental health, and sleep.

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