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Special Article

Special Article

Big data approaches for novel mechanistic insights on sleep and circadian rhythms: a workshop summary

Lawrence Baizer[1,*], Regina Bures[2], Girish Nadkarni[3], Carolyn Reyes-Guzman[4], Sweta Ladwa[2], Brian Cade[5], Michael Brandon Westover[6], Jeffrey Durmer[7], Massimiliano de Zambotti[8], Manisha Desai[9], Ankit Parekh[10], Bing Si[11], Julio Fernandez-Mendoza[12], Kelton Minor[13], Diego R. Mazzotti[14], Soomi Lee[15], Dina Katabi[16], Orsolya Kiss[17], Adam P. Spira[18], Jonna Morris[19], Azizi Seixas[20], Marianthi-Anna Kioumourtzoglou[13], John F. P. Bridges[21], Marishka Brown[1], Lauren Hale[22] and Shaun Purcell[5]

[1]National Center on Sleep Disorders Research, National Heart, Lung and Blood Institute, National Institutes of Health, Bethesda, MD, USA,
[2]National Heart, Lung and Blood Institute, National Institutes of Health, Bethesda, MD, USA,
[3]The Charles Bronfman Institute of Personalized Medicine, Icahn School of Medicine at Mount Sinai, New York, NY, USA,
[4]National Cancer Institute, National Institutes of Health, Bethesda, MD, USA,
[5]Brigham and Women's Hospital, Harvard Medical School, Boston, MA, USA,
[6]Beth Israel Deaconess Medical Center, Harvard Medical School, Boston, MA, USA,
[7]Sleep & Circadian Science, Absolute Rest, Denver, CO, USA,
[8]Science, Ouraring Inc. San Francisco, CA, USA,
[9]Quantitative Sciences Unit, Stanford University Medical School, Stanford, CA, USA,
[10]Division of Pulmonary, Critical Care and Sleep Medicine, Department of Medicine, Icahn School of Medicine at Mount Sinai New York, NY, USA,
[11]School of Computing and Augmented Intelligence, Arizona State University, Tempe, AZ, USA,
[12]Penn State College of Medicine Sleep Research and Treatment Center, Pennsylvania State University College of Medicine, Hershey, PA, USA,
[13]Department of Environmental Health Sciences, Columbia University Mailman School of Public Health, New York, NY, USA,
[14]Division of Medical Informatics, University of Kansas Medical Center, Kansas City, KS, USA,
[15]Department of Human Development and Family Studies, Center for Healthy Aging, Pennsylvania State University, University Park, PA, USA,
[16]MIT Center for Wireless Networks and Mobile Computing, Massachusetts Institute of Technology, Cambridge, MA, USA,
[17]Center for Health Sciences, SRI International, Menlo Park, CA, USA,
[18]Department of Mental Health, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, USA,
[19]School of Nursing, University of Pittsburgh, Pittsburgh, PA, USA,
[20] Department of Psychiatry and Behavioral Sciences, University of Miami, Miami, FL, USA, and
[21]College of Medicine, Ohio State University, Columbus, OH, USA,
[22]Renaissance School of Medicine, Stony Brook University, Stony Brook, NY, USA

[*]Corresponding author. Lawrence Baizer, National Center on Sleep Disorders Research, National Institutes of Health. Bethesda, MD, USA Email: baizerl@nih.gov.

Abstract

The National Center on Sleep Disorders Research of the National Heart, Lung, and Blood Institute at the National Institutes of Health hosted a 2-day virtual workshop titled *Big Data Approaches for Novel Mechanistic Insights on Disorders of Sleep and Circadian Rhythms* on May 2nd and 3rd, 2024. The goals of this workshop were to establish a comprehensive understanding of the current state of sleep and circadian rhythm disorders research to identify opportunities to advance the field by using approaches based on artificial intelligence and machine learning. The workshop showcased rapidly developing technologies for sensitive and comprehensive remote analysis of sleep and its disorders that can account for physiological, environmental, and social influences, potentially leading to novel insights on long-term health consequences of sleep disorders and disparities of these health problems in specific populations.

Key words: sleep; remote monitoring; obstructive sleep apnea; data science; artificial intelligence

Statement of Significance

The continuously evolving field of sleep research holds substantial promise for improving public health by harnessing the power of data science and technology. The integration of a wide variety of sleep-related data sources ranging from public health surveys to outputs from sophisticated wearable sensors permits unprecedented insights into the influences of sleep on overall health and the mechanisms involved. This report summarizes a workshop on Big Data and Sleep conducted by the NIH that showcased the latest developments in the field and identified opportunities for future research.

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The continuously evolving field of sleep research holds substantial promise for improving public health across multiple facets of life by harnessing the power of data science and technology. The integration of a wide variety of sleep-related data sources ranging from public health surveys to outputs from sophisticated wearable sensors permits unprecedented insights into the influences of sleep on overall health and the mechanisms involved. This enhanced understanding has further implications, fostering advancements in cardiovascular, immunological, metabolic, and mental health.

Sleep studies have produced a wealth of rich, multimodal digital data with sources ranging from electronic health records (EHRs) and wearable technology to passive data streams and animal data, comprising a vast trove of information to be harnessed [1–9]. However, there is a growing consensus that this data is not currently being used to its maximum potential. Moreover, this surge in data availability and complexity necessitates robust analytical techniques capable of both handling this volume of data and deriving meaningful insights [10–12]. Accordingly, new artificial intelligence (AI)-based approaches for data analysis are necessary for full utilization of this data.

The evolution of AI began as early as the 1950s with the development of "learning" algorithms capable of developing expertise in playing checkers and automated reasoning algorithms that validated several mathematical theorems. The 1970s and 1980s saw significant advances, setting the stage for the development of more sophisticated AI algorithms [13–15]. In the past 10 years there has been an exponential increase in AI research and applications, including advancements in deep learning [16–18]. At present, AI technology is integral to smart homes, smartphones [19], wearable devices [20], and generates large amounts of digital data [21, 22].

Federal regulations promoting EHRs have catalyzed the use of AI in health care by providing extensive data for analysis. AI tools automate the processing of these data, translating vast amounts into actionable insights, ultimately aiming to improve patient outcomes [23–25] and reduce physician burnout [26]. Additionally, the integration of "Transformers" (a type of neural network architecture that transforms or changes an input sequence into an output sequence) [27–30] and "Generative Pre-trained Transformer" models [31–33] has revolutionized the field. These models process massive data sets from a variety of modalities to enhance data analysis.

AI is currently employed in a variety of healthcare applications, including cardiology, where it has shown promise in interpreting electrocardiograms, potentially surpassing traditional analysis methods in detecting arrhythmias with smaller data samples [22, 23]. The application of transformer models and a variety of technologies for the analysis of these data has enabled significant insights into sleep patterns and anomalies.

In sleep research, the capture of sleep data is facilitated by remote monitoring of sleep and related physiological parameters through the development and use of various innovative devices. Although sleep wearable [34, 35], nearable [36] and airable devices [37] have predominantly been utilized in consumer settings, the feasibility of their integration into clinical environments is increasing. These technologies permit remote clinical sleep monitoring, heralding new possibilities for patient care outside traditional settings. For example, popular devices like Fitbit, which accumulated over 6 billion nights of sleep data [38], have aided in capturing metrics such as sleep duration [39, 40], rapid eye movement cycles [41], and varying sleep patterns [42]. However, despite their widespread use, there are ongoing concerns regarding the quality and reliability of the data these devices produce [43, 44] and whether the data collected is representative of minoritized or underserved populations.

As digital technology permeates everyday life, the ubiquity of smartphones presents a feasible avenue for sleep data collection. Today, smart device interactions are frequent throughout the day, and with many U.S. residents owning fitness trackers, the transition towards integrating these devices into health monitoring, including sleep, is accelerating. Notably, the trend is shifting towards less intrusive monitoring, or airables (devices incorporated into the bedding), indicating a potential shift in consumer preference toward less contact-dependent sleep-tracking methods [45].

Future technological developments will include novel approaches in sensor designs, such as multi-layer electroencephalogram (EEG) tattoos, flexible skin electrodes [46], and wearable devices capable of monitoring a wider range of biological signals (e.g. pulse oximetry, sweat analysis) [47]. Such advancements could facilitate less intrusive and more accurate sleep monitoring.

Wearable devices collect "raw" data directly from their sensors, which may include accelerometry, (measurement of movement), photoplethysmography, (blood flow and heart rate), tracking of body and environmental temperature, and high-granularity pulse rate. This raw data is then processed into aggregated data, yielding insights into sleep structure, circadian rhythms, activity patterns, respiratory metrics, and cardiovascular information [48].

However, there are limitations to remote monitoring approaches. Despite the progress and adoption of these technologies, a significant challenge remains concerning the algorithms used by different companies. Often proprietary, these algorithms operate within "black boxes," making it difficult for researchers to evaluate or improve upon the data analysis and harmonization processes without understanding the algorithmic decision-making involved. This situation can result in variations in the accuracy and reliability of sleep duration measurements and other data derived from these devices [49, 50] and may limit consortia and/or data-sharing opportunities. Challenges associated with the incorporation of wearables and data coordination in clinical trials include integration issues, as wearable data can be difficult to integrate with other clinical variables due to varying data formats and standards. Additionally, ensuring the consistency and accuracy of wearable data when integrated with other clinical data can be difficult [51]. Wearable data are largely collected in free-living settings and are typically noisier than more traditional data, requiring substantial data-cleaning efforts [52]. Standardization and workflow improvements are needed to ensure equitable access to and management of data and to address potential biases and disparities that might worsen due to variations in data collection and integration practices [53, 54]. Finally, the pandemic accelerated interest in decentralized clinical trials, highlighting the importance of accurate data collection from remote participants [55–57].

Insights Achievable With Currently Available Sleep Data Resources

Public data resources including cross-sectional surveys such as the Behavioral Risk Factor Surveillance System [58–60], and the National Health and Nutrition Examination Survey, conducted by the U.S. Census Bureau and the Centers for Disease Control and Prevention, collect data on a variety of sleep parameters, including sleep duration, subjective perception of insufficient rest [61, 62], sleep schedules, disorders, and difficulties [10, 63, 64]. Large-scale cohort studies, such as the All of Us program, provide longitudinal data useful for understanding sleep patterns over time and the resultant long-term health outcomes. Since 1972 the Cancer Prevention Study has followed nearly a million individuals, capturing various data points, including sleep-related information across its multiple cohorts [65]. The National Sleep Research Resource (NSRR) is a rich repository that lends substantial support to sleep studies by providing access to an extensive array of data including physiological signals related to sleep patterns [53, 66, 67].

BioData Catalyst (BDC) is a National Heart, Lung, and Blood Institute-supported data ecosystem which is tailored to support various investigations in heart, lung, blood, and sleep disorders [68, 69]. BDC is a dynamic hub for data integration and sharing, pivotal in fostering collaborative research across multiple studies and facilitating the development of scalable solutions. It supports the construction of custom cohorts within the data and across different studies, adapting to specific research needs. Additionally, functionality is being extended further through the development of a machine learning (ML)-based data model and the integration of an fast healthcare interoperability resources server to enhance EHR data exchange [70, 71].

In the context of clinical and epidemiological research, particularly in sleep studies, handling big data effectively can bring immense value [72, 73]. Traditional sleep monitoring and scoring is labor-intensive and has not changed in decades [74, 75]. Initial studies show that AI models can perform as well or even better than human experts in identifying sleep stages and arousal events during sleep, which could lead to more personalized and accurate sleep medicine [76]. However, before any meaningful analysis can begin, a significant effort is necessary for preparing, cleaning, and harmonizing data from diverse sources. This process is often slow but crucial for ensuring the quality and reliability of the findings.

Integration of Diverse Features of Sleep-Related Information

Newer wearable technologies gather several aspects of sleep-related data that can be integrated to provide a more comprehensive view of sleep health [77]. Addition of metrics like body movement, the menstrual cycle [78, 79], environmental factors (temperature, light), and even brain wave activity from new sensor technologies can increase the information content further [80]. However, consumer-grade wearables, while revolutionary, may not have achieved the level of accuracy and standardization required for rigorous research and clinical usage [37, 81]. Variability between different devices and the lack of standardized data interpretation protocols present significant barriers [82].

Many sleep disorders are diagnosed through self-reports and clinical history [83], while polysomnography (PSG) is indicated in a subset of them. Accordingly, an essential component of evaluating sleep and its disorders is the use of interview data indicating individuals' experience of a good or poor night's sleep and patient-reported outcomes (PROs) [84]. This subjective report is invaluable as it often reflects the real-world nature and impact of sleep disorders on quality of life better than certain objective measures. However, while PROs should be highly valued, a balance of subjective and objective data is necessary for a comprehensive assessment of sleep.

Effects of Disparities, Social Determinants of Health, and Environment Influences on Sleep

Developing an inclusive research framework for sleep health involves considering various disparities and social determinants of health, using wearable and other remote access technology for data collection and engagement, making that technology accessible to underserved populations, and developing precise and personalized health interventions. Extensive, high-quality longitudinal data are essential to understand the full impact of environmental and lifestyle factors on sleep [85, 86]. Considering factors like environment and lifestyle ("life vectors") and their effects on other health outcomes is crucial [87]. Key environmental influences on sleep include temperature, night-time noise, and exposure to artificial light at night [88]. Pathways of impact are both direct (e.g. noise waking you up) and indirect (e.g. environmental exposure-induced stress affecting sleep quality).

Poor air quality (e.g. high levels of pollutants) is another environmental concern as it can result in sleep apnea, respiratory problems, and other disturbances [89]. Air pollution has also been linked to adverse outcomes such as compromised pregnancy outcomes (e.g. low birth weight, preterm birth [90]), neurodevelopmental issues [91], various mood disorders [92], respiratory issues (e.g. asthma [93]), and cardiovascular health problems [94].

Pollution is a leading environmental factor for disability-adjusted life years [95] and is clearly associated with worsened sleep quality [96]. Several models can be used to predict pollution levels at specific locations, but existing models vary and produce different outputs [97, 98]. Bayesian Nonparametric Ensemble can be used to integrate multiple models, as it balances predictive accuracy as it balances input accuracy across input models, providing consistency in predictive performance in space and time and can aid in identifying regions with high measurement uncertainty for targeted monitoring improvements [99, 100]. Community-level assessments have shown that low-income and marginalized communities—for example, communities with a higher proportion of racial/ethnic minority residents—experience both higher pollutant levels [101, 102], as well as higher uncertainty in determining those levels [103].

Poor sleep health can be a cause, risk factor, determinant, or outcome related to various health disorders [104]. Accordingly, it is important to develop precise definitions before crafting targeted interventions and goals. Key considerations include population characteristics, economic opportunities, mobility profiles, environmental, and lifestyle factors as well as light exposure, social jetlag impacts, and seasonal effects. In addition to inappropriate light exposure, pollutants, noise, and temperature, other factors, such as caffeine consumption, sleep routines, and differential healthcare access and stress, social isolation, lifestyle pace, and housing instability should also be considered. Community-focused research involves a digital health equity model [105] as a participant-centric research experience allows the collection of large data sets through remote monitoring devices and equipment.

Both urban and rural areas can have high rates of short sleep duration, which negatively affects public health [106]. However, the issues manifest differently. For example, urban areas may exhibit significant differences in environmental conditions even within close proximity, and adjacent neighborhoods can vary significantly in terms of air pollution, noise levels, temperature, and light pollution, all of which affect sleep [107]. However, relevant data is often collected at a macro level (such as by zip code or neighborhood), which can mask small-scale variations that are crucial for understanding sleep issues and variability. According to the Centers for Disease Control, rural areas report a higher prevalence of issues related to falling and staying asleep, indicating the need for developing robust rural research programs to understand the nuanced sleep challenges that rural communities face [108].

Overall, harmonizing disparate data sources is critical for accurate assessment. The process of collecting and interpreting data poses several challenges, particularly in terms of scale and precision. Data collected at macro levels is useful, but it can overlook the finer details necessary for personalized health interventions. For higher accuracy, data should be collected at the household level whenever possible. Additionally, several studies have indicated that bias in AI is multifaceted, and recognizing its different types is crucial for addressing it effectively [109–111]. For example, there can be bias in the sensors and devices used for data collection, as in the well-known issue of pulse oximeters and different skin tones and thickness [112].

The deployment of AI in healthcare has the potential to either help or harm marginalized communities, depending on how well it is trained and validated. Datasets may have inherent biases and therefore fail to represent the needs of marginalized communities adequately [113]. Accordingly, it is essential to engage communities to ensure AI models are trained on data that accurately reflect their specific needs. Community input can consist of partnerships to involve them in the oversight and development of databases. Constantly integrating patient voices is essential to avoid inaccurate assumptions about community needs.

Data-Based Analytics for New Insights in Sleep Apnea

Sleep disordered breathing (SDB), typically quantified by the apnea-hypopnea index [114, 115] collected during PSG[75, 116], encompasses conditions like sleep apnea. Intensive phenotyping is performed to accurately characterize the full spectrum of the disorder in patients. SDB has notable economic [117] and societal impacts [118] due to its high prevalence and significant health risks if left untreated. Initially, research into SDB genetics focused on the identification of specific genetic markers [119]. Whole-genome sequencing has been used to gain a deeper understanding [120]. This comprehensive approach might yield more effective interventions and therapies due to richer, although currently limited, phenotypic data on smaller cohorts [121, 122]. However, for complex traits such as those observed in SDB, larger sample sizes are crucial. This could be achieved by integrating EHR data [123], which is extensive, relatively low-cost, and chronologically detailed, therefore promising for scaling up research efforts. Innovations like natural language processing (NLP) can help mine unstructured data such as physicians' notes for relevant clinical terms [124–126]. This bolsters the quantity and diversity of data available, simplifies data collection, and increases its feasibility across different regions. However, EHR data are primarily intended for clinical and billing purposes, not research, which presents challenges such as imprecise data and variability in coding.

Obstructive sleep apnea (OSA) has garnered significant attention over the past few years due to its strong association with various cardiovascular diseases (CVDs) [127]. This health relevance is critical given the rising prevalence of both OSA and CVD globally. Intermittent hypoxia, sympathetic activation, oxidative stress, and systemic inflammation are associated with OSA and play significant roles in promoting hypertension, atrial fibrillation, heart failure, and stroke [128–130].

Current studies seek to identify novel biomarkers that could offer new insights into how OSA impacts cardiovascular risk, aiding in early detection, and prevention [131, 132]. Additional elements relevant to clinical and research settings are PROs [133] and diversity in OSA presentation [134]. PROs provide a crucial perspective on the condition's impact beyond physiological measurements. Recognizing the heterogeneity in OSA's presentation is key to developing targeted treatments [135].

Initial studies exploring the relationship between OSA and CVD focused on symptom subtypes in patients with moderate to severe OSA, which can be classified into major symptom clusters [121]. Leveraging resources like the NSRR has been pivotal in describing symptom subtypes and understanding their association with increased incidence of CVD [136]. However, to ensure consistent findings, there is an urgent need to standardize assessment methods and metrics across global studies, as differences in data collection methods may contribute to heterogeneity. Developing open-source tools and standardized parameters can help compare and validate research findings [54].

Towards this goal, researchers developed a decision tree and a minimum set of symptoms, enhancing the identification of at-risk patients [137, 138]. Other studies with real-world data sets, including those from Medicare claims databases, have been leveraged to study the effects of Positive Airway Pressure therapy on cardiovascular risk. Analyses involving ≥888 000 OSA patients revealed that continuous positive airway pressure (CPAP) usage correlated with lower mortality and cardiovascular risk. Consistency in findings across subgroups highlights the robustness of these results [139].

With respect to gender and sex-specific differences in OSA, a key issue is understanding the distinction between sex and gender. Sex refers to biological differences between men and women (e.g. chromosomes, hormone levels, reproductive/sexual anatomy). This is critical in medical research to identify physiological differences that affect disease presentation and treatment. In contrast, gender involves societal roles, behaviors, activities, and attributes that a given culture considers appropriate for men and women. This impacts health outcomes through various psychosocial factors, access to care, and societal expectations.

With respect to integrating multiple factors that might influence sleep disorders, AI, and ML can help identify novel patterns in sleep data, including complex sleep-related signals, such as cardiopulmonary coupling [140]. Furthermore, AI/ML tools can uncover latent biomarkers and predict disorders based on multisource data, which includes physiological signals, such as those captured by sleep EEG, recorded as a component of the PSG and behavior patterns, such as those captured by wearables or actigraphy [141].

AI algorithms can process vast amounts of data more accurately than traditional methods and ML models can predict patterns and abnormalities. Applications in diagnosing sleep disorders include identifying obstructive sleep apnea [142, 143], restless legs syndrome [144, 145], and other disorders (e.g. circadian sleep disorders) and may aid in personalizing treatment plans based on sleep data. It is critical to understand patient experiences and ultimately incorporate patient feedback into treatment evaluations and innovations.

Big Data and AI Offer Insights into the Role of Sleep in Several Chronic Conditions

Obesity is a significant risk factor for cardiovascular disease (CVD), one of the leading causes of mortality globally, and a condition with a multifaceted nature driven by the interplay of biological, environmental, and behavioral factors, which can be effectively captured and integrated through the use of ML algorithms [146]. Adolescence is a critical period for the development of obesity. Habits formed during this developmental stage can persist into adulthood [147], making it essential to identify and mitigate risk factors early. One significant factor influencing obesity in adolescents is sleep behavior [148]. Reduced sleep can lead to decreased physical activity [149] increased negative emotions, greater screen time, and increased food consumption [150], all of which contribute to obesity [151].

Three thousand adolescents wore a Fitbit for three weeks as part of the Adolescent Brain Cognitive Development study. Assessments included cardiovascular fitness using resting heart rate and daily step counts. Sleep metrics included multiple timing, quality, and day-to-day regularity measures. Analysis of the data collected led to the identification of five key interactions defining risk thresholds for obesity across various socio-demographic groups. Notably, interactions between race and heart rate, as well as between economic hardship and sleeping heart rate, highlighted significant variations in obesity risk. These findings emphasize the importance of considering race-specific and socioeconomic factors in understanding obesity risk profiles [146].

The U.S. population is rapidly aging, leading to an increased prevalence of aging-related conditions, including neurodegenerative diseases, such as Alzheimer's disease and related dementias [152]. Older adults commonly experience sleep disturbances, such as insomnia, fragmented sleep, and sleep apnea [153, 154]. Poor sleep is linked to adverse outcomes, including cognitive and functional decline [155–158]. However, sleep disturbances are modifiable risk factors, offering potential intervention opportunities to improve long-term cognitive health.

Integrating wrist actigraphy allowed for the collection of extensive data on sleep and rest/ activity rhythms in a subset of cognitively normal older adults with beta-amyloid deposition in the Anti-Amyloid Treatment in Asymptomatic Alzheimer's Disease (A4) Study and amyloid-negative controls. Applying a data-driven analytic approach to the actigraphy data showed participants who were amyloid-positive had higher average levels of and lower variability in activity in the afternoons across days compared to participants who were amyloid-negative [159]. Notably, these differences were not captured by conventional sleep or circadian metrics. Similar findings emerged in an independent cohort of middle-aged and older adults, supporting the value of data-driven approaches to analysis of rest/activity rhythm data from actigraphy for the purpose of discovery [160].

Traditional methods of measuring brain activity and functions are often limited due to their complexity, cost, and intrusive nature and often require the subject to be in a controlled, laboratory environment. New technologies have been developed to overcome these limitations. For example, a device designed to analyze radio signals that reflect off people and objects in the environment was shown to permit the capture and analysis of the radio signals using AI to extract physiological data such as nocturnal breathing patterns, sleep apnea indicators, body movements, and aberrant motor symptoms related to neurological conditions [161]. This approach allowed for analyzing sleep-related signals in an individuals' home sleep environment and continuously collected data for days at a time, allowing accurate longitudinal analyses. The accuracy of this method was shown to be comparable to results achieved from traditional in laboratory PSG. Using this method, researchers were able to track changes in nocturnal breathing patterns in persons living with Parkinson's disease (PD) By analyzing these patterns in over 7600 individuals, including over 700 with PD, the disorder was detected with high accuracy and specificity. Initial diagnoses were followed up 6 years later to confirm the clinically detectable onset of PD in individuals who were initially undiagnosed but showed early PD symptoms through nocturnal breathing patterns [162].

Ethical, Legal, and Social Implications of AI/ML and big data include safety, transparency, informed consent, potential biases, and data privacy. Further considerations are questions of liability, cybersecurity, intellectual property rights, and more [163]. Ensuring that the public is adequately informed and engaged with emerging technologies is critical [164]. These principles must be included in any use of big data and AI in sleep research.

Summary

There is considerable value in engaging both research and clinical communities in sleep research. The workshop provided strong encouragement for investigators to engage more in transdisciplinary networking opportunities, especially at specialized sleep conferences and meetings, as continued collaboration will lead to meaningful advancements in sleep research and its clinical applications. There is increasing appreciation of the critical role of sleep in overall health. However, recognition of gaps in understanding sleep patterns and behaviors across different demographic groups makes it essential to include existing population-based data sets to fill these knowledge gaps. Ultimately the goal would be to improve health outcomes by harnessing sleep data across different populations and age groups. Use of AI algorithms in this effort would allow comprehensive analysis and understanding of the features that are most significant to consider. There was a robust discussion of the recent progress made in developing and utilizing data sets, sleep monitoring devices, ML models, and environmental assessments and optimism that combining these approaches will enhance understanding and treatment of sleep disorders.

Workshop-Identified Opportunities

Databases containing sleep data

Opportunities include discovering new patterns in data using tools like Transformer models to identify novel sleep features and disorders. Moreover, leveraging transformer models may allow the prediction of cognitive impairments directly from sleep EEG data, thus unlocking deeper understandings of sleep data relations to neurological conditions [165, 166]. Additional opportunities include using AI to analyze large datasets to identify novel patterns and predictors of sleep-related health issues. Efforts could be directed at refining database analyses, including improving the reliability of International Classification of Diseases (ICD) code-based phenotyping by integrating various sources of data like billing codes and healthcare utilization information [167]. Challenges with data source heterogeneity and accurate disease definition can be mitigated by adopting adjusted methods and utilizing innovative tools like NLP. In turn, further developments in NLP could enhance the extraction and categorization of relevant clinical information from unstructured EHR notes.

Wearable, nearable, and airable devices

Future research might focus on comprehensively assessing device performance and identifying the factors that may lead to performance failure. Standards for sleep-tracking devices need to be established [168] and collaboration with industry is essential for progress in this area. The availability of extensive new sources of sleep-related data can lead to the development of new approaches for defining and measuring sleep and sleep disorders. This effort will be facilitated by the development of universal algorithms for sleep characterization, independent of specific devices [169]. It is critical to ensure that sleep data from wearables today will be compatible and interpretable in the future. These efforts may be aided by the establishment of an archive of wearable algorithms for future reference [170–174]. Finally, it will be critical to examine biases in sensor efficacy related to skin color, sensor placement, and recording conditions.

Addressing the heterogeneity of OSA

Including symptom presentation is critical in characterizing OSA heterogeneity. The development and application of better phenotyping tools for OSA are essential for advancing clinical research. Assessing night-to-night variability in OSA severity and its impact on symptom presentation and cardiovascular physiology remains a crucial area for future research. Understanding this variability could refine risk profiles and therapeutic approaches. Understanding sleep health through multiple parameters and diverse research methods may aid in developing targeted interventions to improve the quality of life for those suffering from chronic pain and other long-term disorders [175–177]. Implementation of strategies for broader inclusion in epidemiological studies may improve outcomes through targeted, diverse, and deep phenotyping.

Sleep and the health of populations

Studies might include moving beyond population averages to uncover individual risk profiles and modifying the effects of sleep. With respect to sex and gender differences, rigorous analyses of menopausal status [178], age, and their effect on OSA prevalence in women are essential [179]. NLP could be useful for better identification of menopausal status in research datasets [180]. Physiological differences such as disparities in airway anatomy, muscle function, and hormonal profiles that affect OSA rates between sexes [181] should be investigated further, along with the trend for women to exhibit moderate rather than severe OSA [182, 183]. Analyzing symptom subtypes separately in men and women and then comparing the results can provide more detailed information [184]. This can revolutionize the diagnostic and treatment landscape by improving diagnosis rates with enhanced algorithms to differentiate symptoms and prevalence more accurately. AI could aid in addressing sex differences in cardiovascular outcomes related to OSA, lead to a better understanding of sex-specific differences in sleep patterns [185] and leveraging data to predict CPAP responders.

Linking environmental exposures to sleep and circadian disruptions

Characterizing the role of environmental exposures in sleep and circadian disorders requires the incorporation and assessment of multiple variables and datasets to be managed with consideration of privacy, scalability, and expert guidance. It is essential to ensure that computational resources can handle massive environmental datasets efficiently and at reasonable expense. It is critical to account for spatial and temporal resolution, assessing data on daily, seasonal, or other time scales. Aligning environmental exposure timing with sleep outcomes is also important (e.g. air pollution levels during sleeping hours). Finally, ensuring equitable consideration of disproportionately affected communities and neighborhoods is crucial.

Key overall opportunities

Efforts directed at standardization in sleep research could include standardizing study designs, terminology, and analytical approaches. Establishing a task force for standardizing metrics, sensors, and outcomes is crucial. The development of consistent standards in data collection and analysis methods could be coupled with regular evaluation of methods and results to ensure reliability and accuracy. Collaboration across disciplines, including clinical and data science, is necessary to tackle these complexities. Efforts should be directed towards creating open, collaborative platforms for sharing sleep research data with an emphasis on validating models and devices across diverse populations to avoid biases. It is essential to develop a holistic view of health, employing AI/ML approaches to integrate individual and environmental factors and improve understanding of how these factors interact to influence sleep health. These efforts will be aided by modern AI/ML tools available to manage and analyze complex sleep data. As traditional sleep measures (e.g. one-time self-reported sleep duration) may not fully capture an individual's overall sleep health, greater emphasis should be placed on assessing multiple dimensions of sleep health through both self-reported and objective measures across multiple time points. This approach allows for a more comprehensive evaluation of sleep health, accounting for the often-observed discrepancies between subjective and objective sleep measures [186] and recognizing that sleep health can change over time [187] Recent studies have employed remote multi-night monitoring of actigraphy [188] and sleep EEG [189] to provide more accurate assessments of these issues. Integration of the many factors affecting sleep in combination with AI/ML analyses may lead eventually to improved intervention strategies.

Challenges

AI presents numerous opportunities and challenges in public health, particularly when applied in clinical settings. Challenges include insufficient oversight and the prevalence of false warning messages [190], potential exacerbation of disparities if not properly managed [191], and difficulties in translating AI tools to real-world usage [192]. Accordingly, to control for these problems and concerns AI-based algorithms need to be developed and trained within clinical frameworks. Iterative processes are crucial for refining AI tools to ensure they perform reliably in real-world scenarios, with intervention studies focusing on the interface between AI and human users [193]. Studies need to account for potential biases and the impact of AI on clinician behavior and exam quality [110].

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Data availability

Any research results or data described in this summary can be found in the relevant cited references.

References

1. Baughman DJ. Technology in medicine: optimizing electronic health records. *FP Essent*. 2024;**537**:7–13.
2. Ramesh J, Keeran N, Sagahyroon A, Aloul F. Towards validating the effectiveness of obstructive sleep apnea classification from electronic health records using machine learning. *Healthcare (Basel)*. 2021;**9**(11):1450. doi:10.3390/healthcare9111450
3. Te TT, Keenan BT, Veatch OJ, Boland MR, Hubbard RA, Pack AI. Identifying clusters of patient comorbidities associated with obstructive sleep apnea using electronic health records. *J Clin Sleep Med*. 2024;**20**(4):521–533. doi:10.5664/jcsm.10930
4. Zheng NS, Annis J, Master H, *et al*. Sleep patterns and risk of chronic disease as measured by long-term monitoring with commercial wearable devices in the all of us research program. *Nat Med*. 2024;**30**:2648.
5. Trujillo R, Zhang E, Templeton JM, Poellabauer C. Predicting long-term sleep deprivation using wearable sensors and health surveys. *Comput Biol Med*. 2024;**179**:108749. doi:10.1016/j.compbiomed.2024.108749
6. Sjoland O, Svensson T, Madhawa K, Nt H, Chung UI, Svensson AK. Associations of subjective sleep quality with wearable device-derived resting heart rate during REM sleep and non-REM sleep in a cohort of Japanese office workers. *Nat Sci Sleep*. 2024;**16**:867–877. doi:10.2147/NSS.S455784
7. Frija J, Mullaert J, Abensur Vuillaume L, *et al*. Metrology of two wearable sleep trackers against polysomnography in patients with sleep complaints. *J Sleep Res*. 2024; **2024-06**:e14235. doi:10.1111/jsr.14235
8. Zong S, Du P, Li H, Wang M, Xiao H. Advances in animal models of obstructive sleep apnea. *Front Med (Lausanne)*. 2023;**10**:988752. doi:10.3389/fmed.2023.988752
9. Silva RFO, Pinho BR, Monteiro NM, Santos MM, Oliveira JMA. Automated analysis of activity, sleep, and rhythmic behaviour in various animal species with the Rtivity software. *Sci Rep*. 2022;**12**(1):4179. doi:10.1038/s41598-022-08195-z
10. Yu M, Jiang Y, Gong X, Gao X. Relationship between sleep duration and cognitive function in older adults: analysis of NHANES and UK biobank GWAS data. *Biol Res Nurs*. 2024;**26**(3):399–409. doi:10.1177/10998004241230325
11. Scott H, Naik G, Lechat B, *et al*. Are we getting enough sleep? Frequent irregular sleep found in an analysis of over 11 million nights of objective in-home sleep data. *Sleep Health*. 2024;**10**(1):91–97. doi:10.1016/j.sleh.2023.10.016
12. Mireku MO, Rodriguez A. Sleep duration and waking activities in relation to the national sleep foundation's recommendations: an analysis of US population sleep patterns from 2015 to 2017. *Int J Environ Res Public Health*. 2021;**18**(11):6154. doi:10.3390/ijerph18116154
13. Grzybowski A, Pawlikowska-Lagod K, Lambert WC. A history of artificial intelligence. *Clin Dermatol*. 2024;**42**(3):221–229. doi:10.1016/j.clindermatol.2023.12.016
14. Adami C. A brief history of artificial intelligence research. *Artif Life*. 2021;**27**(2):131–137. doi:10.1162/artl_a_00349
15. Lee T, Natalwala J, Chapple V, Liu Y. A brief history of artificial intelligence embryo selection: from black-box to glass-box. *Hum Reprod*. 2024;**39**(2):285–292. doi:10.1093/humrep/dead254
16. Wang FA, Li Y, Zeng T. Deep learning of radiology-genomics integration for computational oncology: a mini review. *Comput Struct Biotechnol J*. 2024;**23**:2708–2716. doi:10.1016/j.csbj.2024.06.019
17. Swinckels L, Bennis FC, Ziesemer KA, *et al*. The use of deep learning and machine learning on longitudinal electronic health records for the early detection and prevention of diseases: scoping review. *J Med Internet Res*. 2024;**26**:e48320. doi:10.2196/48320
18. Fernandes JND, Cardoso VEM, Comesana-Campos A, Pinheira A. Comprehensive review: machine and deep learning in brain stroke diagnosis. *Sensors (Basel)*. 2024;**24**(13):4355. doi:10.3390/s24134355
19. Dhanak N, Chougule VT, Nalluri K, Kakkad A, Dhimole A, Parihar AS. Artificial intelligence enabled smart phone app for real-time caries detection on bitewing radiographs. *Bioinformation*. 2024;**20**(3):243–247. doi:10.6026/973206300200243
20. Liu Y, Liu C, Gao M, *et al*. Evaluation of a wearable wireless device with artificial intelligence, iThermonitor WT705, for continuous temperature monitoring for patients in surgical wards: a prospective comparative study. *BMJ Open*. 2020;**10**(11):e039474. doi:10.1136/bmjopen-2020-039474
21. Patrascanu OS, Tutunaru D, Musat CL, *et al*. Future horizons: the potential role of artificial intelligence in cardiology. *J Pers Med*. 2024;**14**(6):656. doi:10.3390/jpm14060656
22. Luscher TF, Wenzl FA, D'Ascenzo F, Friedman PA, Antoniades C. Artificial intelligence in cardiovascular medicine: clinical applications. *Eur Heart J*. 2024;**45**:4291.
23. Gala D, Behl H, Shah M, Makaryus AN. The role of artificial intelligence in improving patient outcomes and future of healthcare delivery in cardiology: a narrative review of the literature. *Healthcare (Basel)*. 2024;**12**(4):481. doi:10.3390/healthcare12040481
24. Byrne DW, Domenico HJ, Moore RP. Artificial intelligence for improved patient outcomes-the pragmatic randomized controlled trial is the secret sauce. *Korean J Radiol*. 2024;**25**(2):123–125. doi:10.3348/kjr.2023.1016
25. Ayers JW, Desai N, Smith DM. Regulate artificial intelligence in health care by prioritizing patient outcomes. *JAMA*. 2024;**331**(8):639–640. doi:10.1001/jama.2024.0549
26. Fawzy EM. Using artificial intelligence in electronic health record systems to mitigate physician burnout: a roadmap. *J Healthc Manag*. 2024;**69**(4):244–254.
27. Shickel B, Loftus TJ, Ren Y, Rashidi P, Bihorac A, Ozrazgat-Baslanti T. Digital health transformers and opportunities for artificial intelligence-enabled nephrology. *Clin J Am Soc Nephrol*. 2023;**18**(4):527–529. doi:10.2215/CJN.0000000000000085

28. Pfeffer MA, Ling SSH, Wong JKW. Exploring the frontier: transformer-based models in EEG signal analysis for brain-computer interfaces. *Comput Biol Med*. 2024;**178**:108705. doi:10.1016/j.compbiomed.2024.108705
29. Kumar S, Sumers TR, Yamakoshi T, *et al*. Shared functional specialization in transformer-based language models and the human brain. *Nat Commun*. 2024;**15**(1):5523. doi:10.1038/s41467-024-49173-5
30. Denecke K, May R, Rivera-Romero O. Transformer models in healthcare: a survey and thematic analysis of potentials, shortcomings and risks. *J Med Syst*. 2024;**48**(1):23. doi:10.1007/s10916-024-02043-5
31. Zhu L, Mou W, Xie J, Luo P, Chen R. What is the best approach to assessing generative AI in medicine? *Resuscitation*. 2024;**197**:110164. doi:10.1016/j.resuscitation.2024.110164
32. Platz JJ. Generative AI in clinical medicine: opportunity for improvement. *Ann Thorac Surg*. 2024;**118**:1342. doi:10.1016/j.athoracsur.2024.05.021
33. Loh E. ChatGPT and generative AI chatbots: challenges and opportunities for science, medicine and medical leaders. *BMJ Lead*. 2023;**8**:51–54. doi:10.1136/leader-2023-000797
34. Chiang AA, Jerkins E, Holfinger S, *et al*. OSA diagnosis goes wearable: are the latest devices ready to shine? *J Clin Sleep Med*. 2024;**20**:1823–1838. doi:10.5664/jcsm.11290
35. Niemela M, Maijala A, Nauha L, Jamsa T, Korpelainen R, Farrahi V. Associations of wearable ring measured sleep, sedentary time, and physical activity with cardiometabolic health: a compositional data analysis approach. *Scand J Med Sci Sports*. 2024;**34**(8):e14710. doi:10.1111/sms.14710
36. Yoon H, Choi SH. Technologies for sleep monitoring at home: wearables and nearables. *Biomed Eng Lett*. 2023;**13**(3):313–327. doi:10.1007/s13534-023-00305-8
37. Lee T, Cho Y, Cha KS, *et al*. Accuracy of 11 wearable, nearable, and airable consumer sleep trackers: prospective multicenter validation study. *JMIR Mhealth Uhealth*. 2023;**11**:e50983. doi:10.2196/50983
38. Ong JL, Tandi J, Patanaik A, Lo JC, Chee MWL. Large-scale data from wearables reveal regional disparities in sleep patterns that persist across age and sex. *Sci Rep*. 2019;**9**(1):3415. doi:10.1038/s41598-019-40156-x
39. Rezaei N, Grandner MA. Changes in sleep duration, timing, and variability during the COVID-19 pandemic: large-scale Fitbit data from 6 major US cities. *Sleep Health*. 2021;**7**(3):303–313. doi:10.1016/j.sleh.2021.02.008
40. Liao Y, Robertson MC, Winne A, *et al*. Investigating the within-person relationships between activity levels and sleep duration using Fitbit data. *Transl. Behav. Med.*. 2021;**11**(2):619–624. doi:10.1093/tbm/ibaa071
41. von Gall C, Holub L, Ali AAH, Eickhoff S. Timing of deep and REM sleep based on Fitbit sleep staging in young healthy adults under real-life conditions. *Brain Sci*. 2024;**14**(3):260. doi:10.3390/brainsci14030260
42. Lau T, Ong JL, Ng BKL, *et al*. Minimum number of nights for reliable estimation of habitual sleep using a consumer sleep tracker. *Sleep Adv*. 2022;**3**(1):zpac026. doi:10.1093/sleepadvances/zpac026
43. Rowe VT, Neville M. Measuring reliability of movement with accelerometry: Fitbit versus ActiGraph. *Am J Occup Ther*. 2019;**73**(2):7302205150p1–7302205150p6. doi:10.5014/ajot.2019.030692
44. Eylon G, Tikotzky L, Dinstein I. Performance evaluation of Fitbit charge 3 and actigraphy vs. polysomnography: sensitivity, specificity, and reliability across participants and nights. *Sleep Health*. 2023;**9**(4):407–416. doi:10.1016/j.sleh.2023.04.001
45. Ravindran KKG, Della Monica C, Atzori G, *et al*. Contactless and longitudinal monitoring of nocturnal sleep and daytime naps in older men and women: a digital health technology evaluation study. *Sleep*. 2023;**46**(10). doi:10.1093/sleep/zsad194
46. Zhang L, Kumar KS, He H, *et al*. Fully organic compliant dry electrodes self-adhesive to skin for long-term motion-robust epidermal biopotential monitoring. *Nat Commun*. 2020;**11**(1):4683. doi:10.1038/s41467-020-18503-8
47. Galliani M, Ferrari LM, Ismailova E. Conformable wearable electrodes: from fabrication to electrophysiological assessment. *J Vis Exp*. 2022;**2022**(185):video.
48. Lu H, Feng X, Zhang J. Early detection of cardiorespiratory complications and training monitoring using wearable ECG sensors and CNN. *BMC Med Inform Decis Mak*. 2024;**24**(1):194. doi:10.1186/s12911-024-02599-9
49. Neishabouri A, Nguyen J, Samuelsson J, *et al*. Quantification of acceleration as activity counts in ActiGraph wearable. *Sci Rep*. 2022;**12**(1):11958. doi:10.1038/s41598-022-16003-x
50. Weaver RG, de Zambotti M, White J, *et al*. Evaluation of a device-agnostic approach to predict sleep from raw accelerometry data collected by Apple Watch Series 7, Garmin Vivoactive 4, and ActiGraph GT9X Link in children with sleep disruptions. *Sleep Health*. 2023;**9**(4):417–429. doi:10.1016/j.sleh.2023.04.005
51. Effah Kaufmann E, Tackie R, Pitt JB, *et al*. Feasibility of leveraging consumer wearable devices with data platform integration for patient vital monitoring in low-resource settings. *Int J Telemed Appl*. 2024;**2024**:8906413. doi:10.1155/2024/8906413
52. Ortiz BL, Gupta V, Kumar R, *et al*. Data preprocessing techniques for artificial learning (AI)/machine learning (ML)-readiness: systematic review of wearable sensor data in cancer care. *JMIR Mhealth Uhealth*. 2024;**12**:e59587. doi:10.2196/59587
53. Zhang Y, Kim M, Prerau M, *et al*. The National Sleep Research Resource: making data findable, accessible, interoperable, reusable and promoting sleep science. *Sleep*. 2024;**47**(7). doi:10.1093/sleep/zsae088
54. Baumert M, Cowie MR, Redline S, *et al*. Sleep characterization with smart wearable devices: a call for standardization and consensus recommendations. *Sleep*. 2022;**45**(12). doi:10.1093/sleep/zsac183
55. Underhill C, Freeman J, Dixon J, *et al*. Decentralized clinical trials as a new paradigm of trial delivery to improve equity of access. *JAMA Oncol*. 2024;**10**(4):526–530. doi:10.1001/jamaoncol.2023.6565
56. McCarthy MW, Lindsell CJ, Rajasingham R, Stewart TG, Boulware DR, Naggie S. Progress toward realizing the promise of decentralized clinical trials. *J Clin Transl Sci*. 2024;**8**(1):e19. doi:10.1017/cts.2023.706
57. Daly B, Brawley OW, Gospodarowicz MK, *et al*. Remote monitoring and data collection for decentralized clinical trials. *JAMA Netw Open*. 2024;**7**(4):e246228. doi:10.1001/jamanetworkopen.2024.6228
58. Brault MW, Wittenborn JS, Rein DB. Behavioral risk factor surveillance system and American community survey estimates of vision difficulty prevalence. *JAMA Ophthalmol*. 2024;**142**(8):768–771. doi:10.1001/jamaophthalmol.2024.1993
59. Wesselbaum D. Association of hypertension with well-being: results from the behavioral risk factor surveillance system (BRFSS) study. *High Blood Press Cardiovasc Prev*. 2024;**31**(4):401–404. doi:10.1007/s40292-024-00653-1
60. Town M, Eke P, Zhao G, *et al*. Racial and ethnic differences in social determinants of health and health-related social needs

among adults—behavioral risk factor surveillance system, United States, 2022. *MMWR Morb Mortal Wkly Rep*. 2024;**73**(9):204–208. doi:10.15585/mmwr.mm7309a3
61. Okoro CA, Courtney-Long E, Cyrus AC, Zhao G, Wheaton AG. Self-reported short sleep duration among US adults by disability status and functional disability type: results from the 2016 behavioral risk factor surveillance system. *Disabil Health J*. 2020;**13**(3):100887. doi:10.1016/j.dhjo.2020.100887
62. Ogugu EG, Reilly MR, Mbe KTA, Bell JF. Habitual sleep duration and health-related quality of life in family caregivers: findings from the behavioral risk factor surveillance system. *Behav Sleep Med*. 2024;**22**(4):499–515. doi:10.1080/15402002.2024.2314284
63. Xie X, Zheng X, Mei L, *et al*. Association between sleep duration and subjective memory complaints: a large-scale cross-sectional study based on NHANES. *Prev Med Rep*. 2024;**43**:102790. doi:10.1016/j.pmedr.2024.102790
64. Sun H, Li S. Exploring the relationship between smoking and poor sleep quality: a cross-sectional study using NHANES. *Front Psychiatry*. 2024;**15**:1407741. doi:10.3389/fpsyt.2024.1407741
65. Donzella SM, Masters M, Phipps AI, Patel AV, Zhong C. Validity of self-reported sleep duration in the Cancer Prevention Study-3. *PLoS One*. 2024;**19**(8):e0307409. doi:10.1371/journal.pone.0307409
66. Zhang GQ, Cui L, Mueller R, *et al*. The National Sleep Research Resource: towards a sleep data commons. *J Am Med Inform Assoc*. 2018;**25**(10):1351–1358. doi:10.1093/jamia/ocy064
67. Purcell SM, Manoach DS, Demanuele C, *et al*. Characterizing sleep spindles in 11,630 individuals from the National Sleep Research Resource. *Nat Commun*. 2017;**8**:15930. doi:10.1038/ncomms15930
68. de Vries PS, Conomos MP, Singh K, *et al*. Whole-genome sequencing uncovers two loci for coronary artery calcification and identifies ARSE as a regulator of vascular calcification. *Nat Cardiovasc Res*. 2023;**2**(12):1159–1172. doi:10.1038/s44161-023-00375-y
69. Akinyemi RO, Tiwari HK, Srinivasasainagendra V, *et al*.; SIREN Team. Novel functional insights into ischemic stroke biology provided by the first genome-wide association study of stroke in indigenous Africans. *Genome Med*. 2024;**16**(1):25. doi:10.1186/s13073-023-01273-5
70. Lanyi L, Rinner C. ELGA terminology server for clinical decision support: a case-study using an existing knowledge base, CDS hooks and FHIR. *Stud Health Technol Inform*. 2023;**301**:125–130. doi:10.3233/SHTI230025
71. Jathissa P, Rohatsch L, Sauermann S, Hussein R. OMOP-on-FHIR: a FHIR server development to facilitate data interaction with the OMOP-CDM and FHIR for PGHD. *Stud Health Technol Inform*. 2024;**316**:157–158. doi:10.3233/SHTI240367
72. Li X, Cui L, Zhang GQ, Lhatoo SD. Can big data guide prognosis and clinical decisions in epilepsy? *Epilepsia*. 2021;**62**(Suppl 2):S106–S115. doi:10.1111/epi.16786
73. Chouhan U, Sahu RK, Bhatt S, Kurmi S, Choudhari JK. Emerging trends in big data analysis in computational biology and bioinformatics in health informatics: a case study on epilepsy and seizures. *Methods Mol Biol*. 2024;**2719**:99–119. doi:10.1007/978-1-0716-3461-5_6
74. Schenck CH, Mahowald MW. Insights into polysomnography-confirmed rapid eye movement sleep behavior disorder from new prevalence and gender data in the general population. *Sleep*. 2018;**41**(2). doi:10.1093/sleep/zsy020
75. Mullins AE, Pehel S, Parekh A, *et al*. The stability of slow-wave sleep and EEG oscillations across two consecutive nights of laboratory polysomnography in cognitively normal older adults. *J Sleep Res*. 2024;**34**:e14281. doi:10.1111/jsr.14281
76. Goldstein CA, Berry RB, Kent DT, *et al*. Artificial intelligence in sleep medicine: background and implications for clinicians. *J Clin Sleep Med*. 2020;**16**(4):609–618. doi:10.5664/jcsm.8388
77. Roberts DM, Schade MM, Mathew GM, Gartenberg D, Buxton OM. Detecting sleep using heart rate and motion data from multisensor consumer-grade wearables, relative to wrist actigraphy and polysomnography. *Sleep*. 2020;**43**(7). doi:10.1093/sleep/zsaa045
78. Alzueta E, Gombert-Labedens M, Javitz H, *et al*. Menstrual cycle variations in wearable-detected finger temperature and heart rate, but not in sleep metrics, in young and midlife individuals. *J Biol Rhythms*. 2024;**39**(5):395–412. doi:10.1177/07487304241265018
79. Alzueta E, de Zambotti M, Javitz H, *et al*. Tracking sleep, temperature, heart rate, and daily symptoms across the menstrual cycle with the oura ring in healthy women. *Int J Womens Health*. 2022;**14**:491–503. doi:10.2147/IJWH.S341917
80. Edgley K, Chun HY, Whiteley WN, Tsanas A. New insights into stroke from continuous passively collected temperature and sleep data using wrist-worn wearables. *Sensors (Basel)*. 2023;**23**(3):1069. doi:10.3390/s23031069
81. Kainec KA, Caccavaro J, Barnes M, Hoff C, Berlin A, Spencer RMC. Evaluating accuracy in five commercial sleep-tracking devices compared to research-grade actigraphy and polysomnography. *Sensors (Basel)*. 2024;**24**(2):635. doi:10.3390/s24020635
82. Helmer P, Hottenrott S, Wienboker K, *et al*. Reliability of continuous vital sign monitoring in post-operative patients employing consumer-grade fitness trackers: a randomised pilot trial. *Digit Health*. 2024;**10**:20552076241254026. doi:10.1177/20552076241254026
83. Espie CA, Kyle SD, Hames P, Gardani M, Fleming L, Cape J. The sleep condition indicator: a clinical screening tool to evaluate insomnia disorder. *BMJ Open*. 2014;**4**(3):e004183. doi:10.1136/bmjopen-2013-004183
84. Wang W, Peng H, Bouak F. Measuring sleep parameters of naval sailors: a comparison between subjective self-report and wrist actigraphy. *Appl Ergon*. 2022;**102**:103744. doi:10.1016/j.apergo.2022.103744
85. Kuriyama K. Social determinants of sleep quality: association between sleep quality and living environment among older individuals. *Sleep Biol Rhythms*. 2024;**22**(3):301–302. doi:10.1007/s41105-024-00533-0
86. Sun Y, Yang J, Xia Y, *et al*. Association of healthy lifestyle with self-reported sleep disordered breathing: a cross-sectional study. *Sleep Med*. 2024;**119**:352–356. doi:10.1016/j.sleep.2024.05.026
87. Savcisens G, Eliassi-Rad T, Hansen LK, *et al*. Using sequences of life-events to predict human lives. *Nat Comput Sci*. 2024;**4**(1):43–56. doi:10.1038/s43588-023-00573-5
88. Helbich M, Burov A, Dimitrova D, Markevych I, Nieuwenhuijsen MJ, Dzhambov AM. Sleep problems mediate the association between outdoor light pollution and symptoms of depression and anxiety: a cross-sectional, multi-city study in Bulgaria. *Environ Res*. 2024;**263**:119897. doi:10.1016/j.envres.2024.119897
89. Carandina A, Fanti G, Carminati A, *et al*. Indoor air pollution impacts cardiovascular autonomic control during sleep and the inflammatory profile. *Environ Res*. 2024;**260**:119783. doi:10.1016/j.envres.2024.119783
90. Herrera T, Seok E, Cowell W, *et al*. Redlining in New York City: impacts on particulate matter exposure during pregnancy and birth outcomes. *J Epidemiol Community Health*. 2024;**79**:12–18. doi:10.1136/jech-2024-222134
91. Campbell DB. Air pollution exposure during pregnancy increases risk of neurodevelopmental disorders. *Dev Med Child Neurol*. 2023;**65**(6):728–729. doi:10.1111/dmcn.15511

92. Zhang X, Ding L, Yang F, *et al*. Association between indoor air pollution and depression: a systematic review and meta-analysis of cohort studies. *BMJ Open*. 2024;**14**(5):e075105. doi:10.1136/bmjopen-2023-075105
93. Wang J, Cortes-Ramirez J, Gan T, Davies JM, Hu W. Effects of climate and environmental factors on childhood and adolescent asthma: a systematic review based on spatial and temporal analysis evidence. *Sci Total Environ*. 2024;**951**:175863. doi:10.1016/j.scitotenv.2024.175863
94. Zhou H, Hong F, Wang L, *et al*.; China Multi-Ethnic Cohort (CMEC). Air pollution and risk of 32 health conditions: outcome-wide analyses in a population-based prospective cohort in Southwest China. *BMC Med*. 2024;**22**(1):370. doi:10.1186/s12916-024-03596-5
95. Hahad O, Lelieveld J, Al-Kindi S, *et al*. Burden of disease in Germany attributed to ambient particulate matter pollution: findings from the global burden of disease study 2019. *Herz*. 2024;**50**:42–50. doi:10.1007/s00059-024-05269-8
96. He F, Yanosky JD, Bixler EO, *et al*. Short-term and intermediate-term fine particulate air pollution are synergistically associated with habitual sleep variability in adolescents—a cross-sectional study. *Environ Res*. 2023;**227**:115726. doi:10.1016/j.envres.2023.115726
97. Di Q, Amini H, Shi L, *et al*. An ensemble-based model of PM(2.5) concentration across the contiguous United States with high spatiotemporal resolution. *Environ Int*. 2019;**130**:104909. doi:10.1016/j.envint.2019.104909
98. Shi Y, Bilal M, Ho HC, Omar A. Urbanization and regional air pollution across South Asian developing countries—a nationwide land use regression for ambient PM(2.5) assessment in Pakistan. *Environ Pollut*. 2020;**266**(Pt 2):115145. doi:10.1016/j.envpol.2020.115145
99. Wei Z, Mukherjee S. Health-behaviors associated with the growing risk of adolescent suicide attempts: a data-driven cross-sectional study. *Am J Health Promot*. 2021;**35**(5):688–693. doi:10.1177/0890117120977378
100. Bonato V, Baladandayuthapani V, Broom BM, Sulman EP, Aldape KD, Do KA. Bayesian ensemble methods for survival prediction in gene expression data. *Bioinformatics*. 2011;**27**(3):359–367. doi:10.1093/bioinformatics/btq660
101. Du C, Liu W. Defending against environmental threats: unveiling household adaptation strategies and population heterogeneity. *Environ Int*. 2024;**190**:108858. doi:10.1016/j.envint.2024.108858
102. Del Pozzo J, Kouba I, Alvarez A, O'Sullivan-Bakshi T, Krishnamoorthy K, Blitz MJ. Environmental justice index and adverse pregnancy outcomes. *AJOG Glob Rep*. 2024;**4**(1):100330. doi:10.1016/j.xagr.2024.100330
103. Belanoff C, Black A, Ncube CN, Acevedo-Garcia D, Almeida J. Neighborhood child opportunity and preterm birth rates by race and ethnicity. *JAMA Netw Open*. 2024;**7**(9):e2432766. doi:10.1001/jamanetworkopen.2024.32766
104. Cavailles C, Wallace M, Leng Y, Stone KL, Ancoli-Israel S, Yaffe K. Multidimensional sleep profiles via machine learning and risk of dementia and cardiovascular disease. *medRxiv*. 2024. doi:10.1101/2024.08.19.24312248
105. Bucher A, Chaudhry BM, Davis JW, *et al*. How to design equitable digital health tools: a narrative review of design tactics, case studies, and opportunities. *PLOS Digit Health*. 2024;**3**(8):e0000591. doi:10.1371/journal.pdig.0000591
106. Liu D, He J, Li H. The relationship between adolescents' physical activity, circadian rhythms, and sleep. *Front Psychiatry*. 2024;**15**:1415985. doi:10.3389/fpsyt.2024.1415985
107. Yang L, Qin C, Li K, Deng C, Liu Y. Quantifying the spatiotemporal heterogeneity of PM(2.5) pollution and its determinants in 273 cities in China. *Int J Environ Res Public Health*. 2023;**20**(2):1183. doi:10.3390/ijerph20021183
108. Tovar A, Chui K, Hyatt RR, *et al*. Healthy-lifestyle behaviors associated with overweight and obesity in US rural children. *BMC Pediatr*. 2012;**12**:102. doi:10.1186/1471-2431-12-102
109. Stanley EAM, Souza R, Winder AJ, *et al*. Towards objective and systematic evaluation of bias in artificial intelligence for medical imaging. *J Am Med Inform Assoc*. 2024;**31**:2613–2621. doi:10.1093/jamia/ocae165
110. Mihan A, Pandey A, Van Spall HG. Mitigating the risk of artificial intelligence bias in cardiovascular care. *Lancet Digit Health*. 2024;**6**:e749–e754. doi:10.1016/s2589-7500(24)00155-9
111. Kocak B, Ponsiglione A, Stanzione A, *et al*. Bias in artificial intelligence for medical imaging: fundamentals, detection, avoidance, mitigation, challenges, ethics, and prospects. *Diagn Interv Radiol*. 2024.
112. Hao S, Dempsey K, Matos J, *et al*. Utility of skin tone on pulse oximetry in critically ill patients: a prospective cohort study. *Crit Care Explor*. 2024;**6**(9):e1133. doi:10.1097/CCE.0000000000001133
113. Franklin G, Stephens R, Piracha M, *et al*. The sociodemographic biases in machine learning algorithms: a biomedical informatics perspective. *Life (Basel)*. 2024;**14**(6):652. doi:10.3390/life14060652
114. Martinot JB, Le-Dong NN, Tamisier R, Bailly S, Pepin JL. Determinants of apnea-hypopnea index variability during home sleep testing. *Sleep Med*. 2023;**111**:86–93. doi:10.1016/j.sleep.2023.09.002
115. Kim S, Choi HS, Kim D, *et al*. A Comprehensive study on a deep-learning-based electrocardiography analysis for estimating the apnea-hypopnea index. *Diagnostics (Basel)*. 2024;**14**(11):1134. doi:10.3390/diagnostics14111134
116. Grassi M, Dacco S, Caldirola D, Perna G, Schruers K, Defillo A. Enhanced sleep staging with artificial intelligence: a validation study of new software for sleep scoring. *Front Artif Intell*. 2023;**6**:1278593. doi:10.3389/frai.2023.1278593
117. Borsoi L, Armeni P, Donin G, Costa F, Ferini-Strambi L. The invisible costs of obstructive sleep apnea (OSA): systematic review and cost-of-illness analysis. *PLoS One*. 2022;**17**(5):e0268677. doi:10.1371/journal.pone.0268677
118. Tolley K, Noble-Longster J, Mettam S, *et al*. Exploring the impact of excessive daytime sleepiness caused by obstructive sleep apnea on patient and partner quality of life: a time trade-off utility study in the UK general public. *J Clin Sleep Med*. 2022;**18**(9):2237–2246. doi:10.5664/jcsm.10092
119. Zhou R, Suo C, Jiang Y, *et al*. Association of sleep pattern and genetic susceptibility with obstructive sleep apnea: a prospective analysis of the UK biobank. *Nat Sci Sleep*. 2024;**16**:503–515. doi:10.2147/NSS.S443721
120. Liang J, Wang H, Cade BE, *et al*.; TOPMed Sleep Working Group. Targeted genome sequencing identifies multiple rare variants in caveolin-1 associated with obstructive sleep apnea. *Am J Respir Crit Care Med*. 2022;**206**(10):1271–1280. doi:10.1164/rccm.202203-0618OC
121. Fontanilles Arbones E, Salord Oleo N, Gasa Galmes M, *et al*. Phenotypes of obstructive sleep apnea in women: a real-life cohort study. *Sleep Med*. 2024;**121**:295–302. doi:10.1016/j.sleep.2024.07.016
122. Hang LW, Tsai YC, Finnsson E, Agustsson JS, Sands SA, Cheng WJ. Sex-specific age-related worsening of pathological endotypic traits in patients with obstructive sleep apnea. *Sleep*. 2024;(1):185. doi:10.1093/sleep/zsae185

123. Veatch OJ, Bauer CR, Keenan BT, *et al*. Characterization of genetic and phenotypic heterogeneity of obstructive sleep apnea using electronic health records. *BMC Med Genomics*. 2020;**13**(1):105. doi:10.1186/s12920-020-00755-4
124. Chen J, Druhl E, Polepalli Ramesh B, *et al*. A natural language processing system that links medical terms in electronic health record notes to lay definitions: system development using physician reviews. *J Med Internet Res*. 2018;**20**(1):e26. doi:10.2196/jmir.8669
125. Liao KP, Cai T, Savova GK, *et al*. Development of phenotype algorithms using electronic medical records and incorporating natural language processing. *BMJ*. 2015;**350**:h1885. doi:10.1136/bmj.h1885
126. Cade BE, Hassan SM, Dashti HS, *et al*. Sleep apnea phenotyping and relationship to disease in a large clinical biobank. *JAMIA Open*. 2022;**5**(1):ooab117. doi:10.1093/jamiaopen/ooab117
127. DiCaro MV, Lei K, Yee B, Tak T. The effects of obstructive sleep apnea on the cardiovascular system: a comprehensive review. *J Clin Med*. 2024;**13**(11):3223. doi:10.3390/jcm13113223
128. Yasuma F, Noda A, Hayano J. Blood pressure regulation and hypertension in obstructive sleep apnea syndrome: a historical perspective. *Intern Med*. 2024;**63**:3131–3136. doi:10.2169/internalmedicine.2960-23
129. Holtstrand Hjalm H, Thunstrom E, Glantz H, Karlsson M, Celik Y, Peker Y. Obstructive sleep apnea severity and prevalent atrial fibrillation in a sleep clinic cohort with versus without excessive daytime sleepiness. *Sleep Med*. 2023;**112**:63–69. doi:10.1016/j.sleep.2023.09.012
130. Banjade P, Kandel K, Itani A, *et al*. The interplay between obstructive sleep apnea, chronic obstructive pulmonary disease, and congestive heart failure: time to collectively refer to them as triple overlap syndrome? *Medicina (Kaunas)*. 2023;**59**(8):1374. doi:10.3390/medicina59081374
131. Yu B, Wei J, Zhao J, *et al*. The neutrophil-to-lymphocyte ratio is a potential biomarker for the occurrence of atrial fibrillation in patients with obstructive sleep apnea: a biomarker of af in osa patients. *Sleep Med*. 2023;**110**:259–267. doi:10.1016/j.sleep.2023.08.004
132. Diaz-Garcia E, Garcia-Sanchez A, Sanz-Rubio D, *et al*. SMAD4 expression in monocytes as a potential biomarker for atherosclerosis risk in patients with obstructive sleep apnea. *Int J Mol Sci*. 2023;**24**(9):7900.
133. Pevernagie D, Bauters FA, Hertegonne K. The role of patient-reported outcomes in sleep measurements. *Sleep Med Clin*. 2021;**16**(4):595–606. doi:10.1016/j.jsmc.2021.07.001
134. Gauld C, Baillieul S, Martin VP, *et al*. Symptom content analysis of OSA questionnaires: time to identify and improve relevance of diversity of OSA symptoms? *J Clin Sleep Med*. 2024;**20**(7):1105–1117. doi:10.5664/jcsm.11086
135. Aishah A, Tong BKY, Osman AM, *et al*. Stepwise add-on and endotype-informed targeted combination therapy to treat obstructive sleep apnea: a proof-of-concept study. *Ann Am Thorac Soc*. 2023;**20**(9):1316–1325. doi:10.1513/AnnalsATS.202210-892OC
136. Hui X, Cao W, Xu Z, Guo J, Luo J, Xiao Y. Hypoxic indices for obstructive sleep apnoea severity and cardiovascular disease risk prediction: a comparison and application in a community population. *Respirology*. 2024;**29**(9):825–834. doi:10.1111/resp.14754
137. Dai R, Yang K, Zhuang J, *et al*. Enhanced machine learning approaches for OSA patient screening: model development and validation study. *Sci Rep*. 2024;**14**(1):19756. doi:10.1038/s41598-024-70647-5
138. Sheta A, Thaher T, Surani SR, *et al*. Diagnosis of obstructive sleep apnea using feature selection, classification methods, and data grouping based age, sex, and race. *Diagnostics (Basel)*. 2023;**13**(14):2417. doi:10.3390/diagnostics13142417
139. Mazzotti DR, Waitman LR, Miller J, *et al*.; Greater Plains Collaborative. Positive airway pressure, mortality, and cardiovascular risk in older adults with sleep apnea. *JAMA Netw Open*. 2024;**7**(9):e2432468. doi:10.1001/jamanetworkopen.2024.32468
140. Tripathy RK, Gajbhiye P, Acharya UR. Automated sleep apnea detection from cardio-pulmonary signal using bivariate fast and adaptive EMD coupled with cross time-frequency analysis. *Comput Biol Med*. 2020;**120**:103769. doi:10.1016/j.compbiomed.2020.103769
141. Mazzotti DR. Multimodal integration of sleep electroencephalogram, brain imaging, and cognitive assessments: approaches using noisy clinical data. *Sleep*. 2024;**47**(2). doi:10.1093/sleep/zsad305
142. Brennan HL, Kirby SD. The role of artificial intelligence in the treatment of obstructive sleep apnea. *J Otolaryngol Head Neck Surg*. 2023;**52**(1):7. doi:10.1186/s40463-023-00621-0
143. Kang C, An S, Kim HJ, *et al*. Age-integrated artificial intelligence framework for sleep stage classification and obstructive sleep apnea screening. *Front Neurosci*. 2023;**17**:1059186. doi:10.3389/fnins.2023.1059186
144. Schormair B, Zhao C, Bell S, *et al*.; 23andMe Research Team. Genome-wide meta-analyses of restless legs syndrome yield insights into genetic architecture, disease biology and risk prediction. *Nat Genet*. 2024;**56**(6):1090–1099. doi:10.1038/s41588-024-01763-1
145. Kim M, Kim H, Seo P, Jung KY, Kim KH. Explainable machine-learning-based characterization of abnormal cortical activities for working memory of restless legs syndrome patients. *Sensors (Basel)*. 2022;**22**(20):7792. doi:10.3390/s22207792
146. Kiss O, Baker FC, Palovics R, Dooley EE, Pettee Gabriel K, Nagata JM. Using explainable machine learning and Fitbit data to investigate predictors of adolescent obesity. *Sci Rep*. 2024;**14**(1):12563. doi:10.1038/s41598-024-60811-2
147. Guo SS, Wu W, Chumlea WC, Roche AF. Predicting overweight and obesity in adulthood from body mass index values in childhood and adolescence. *Am J Clin Nutr*. 2002;**76**(3):653–658. doi:10.1093/ajcn/76.3.653
148. Fatima Y, Doi SA, Mamun AA. Longitudinal impact of sleep on overweight and obesity in children and adolescents: a systematic review and bias-adjusted meta-analysis. *Obes Rev*. 2015;**16**(2):137–149. doi:10.1111/obr.12245
149. Semplonius T, Willoughby T. Long-term links between physical activity and sleep quality. *Med Sci Sports Exerc*. 2018;**50**(12):2418–2424. doi:10.1249/MSS.0000000000001706
150. Dashti HS, Scheer FA, Jacques PF, Lamon-Fava S, Ordovas JM. Short sleep duration and dietary intake: epidemiologic evidence, mechanisms, and health implications. *Adv Nutr*. 2015;**6**(6):648–659. doi:10.3945/an.115.008623
151. Nagata JM, Smith N, Alsamman S, *et al*. Association of physical activity and screen time with body mass index among US adolescents. *JAMA Netw Open*. 2023;**6**(2):e2255466. doi:10.1001/jamanetworkopen.2022.55466
152. Hebert LE, Weuve J, Scherr PA, Evans DA. Alzheimer disease in the United States (2010-2050) estimated using the 2010 census. *Neurology*. 2013;**80**(19):1778–1783. doi:10.1212/WNL.0b013e31828726f5
153. Ancoli-Israel S, Kripke DF, Klauber MR, Mason WJ, Fell R, Kaplan O. Sleep-disordered breathing in community-dwelling elderly. *Sleep*. 1991;**14**(6):486–495. doi:10.1093/sleep/14.6.486

154. Li J, Vitiello MV, Gooneratne NS. Sleep in normal aging. *Sleep Med Clin*. 2022;**17**(2):161–171. doi:10.1016/j.jsmc.2022.02.007
155. Foley DJ, Monjan AA, Brown SL, Simonsick EM, Wallace RB, Blazer DG. Sleep complaints among elderly persons: an epidemiologic study of three communities. *Sleep*. 1995;**18**(6):425–432. doi:10.1093/sleep/18.6.425
156. Diem SJ, Blackwell TL, Stone KL, *et al*. Measures of sleep-wake patterns and risk of mild cognitive impairment or dementia in older women. *Am J Geriatr Psychiatry*. 2016;**24**(3):248–258. doi:10.1016/j.jagp.2015.12.002
157. Lim AS, Kowgier M, Yu L, Buchman AS, Bennett DA. Sleep fragmentation and the risk of incident Alzheimer's disease and cognitive decline in older persons. *Sleep*. 2013;**36**(7):1027–1032. doi:10.5665/sleep.2802
158. Yaffe K, Laffan AM, Harrison SL, *et al*. Sleep-disordered breathing, hypoxia, and risk of mild cognitive impairment and dementia in older women. *JAMA*. 2011;**306**(6):613–619. doi:10.1001/jama.2011.1115
159. Spira AP, Zipunnikov V, Raman R, *et al*. Brain amyloid burden, sleep, and 24-hour rest/activity rhythms: screening findings from the Anti-amyloid treatment in asymptomatic Alzheimer's and longitudinal evaluation of amyloid risk and neurodegeneration studies. *Sleep Adv*. 2021;**2**(1):zpab015. doi:10.1093/sleepadvances/zpab015
160. Spira AP, Liu F, Zipunnikov V, *et al*. Evaluating a novel 24-hour rest/activity rhythm marker of preclinical beta-amyloid deposition. *Sleep*. 2024;**47**(5). doi:10.1093/sleep/zsae037
161. Kabelac Z, Tarolli CG, Snyder C, *et al*. Passive monitoring at home: a pilot study in Parkinson disease. *Digit Biomark*. 2019;**3**(1):22–30. doi:10.1159/000498922
162. Yang Y, Yuan Y, Zhang G, *et al*. Artificial intelligence-enabled detection and assessment of Parkinson's disease using nocturnal breathing signals. *Nat Med*. 2022;**28**(10):2207–2215. doi:10.1038/s41591-022-01932-x
163. Gerke S, Babic B, Evgeniou T, Cohen IG. The need for a system view to regulate artificial intelligence/machine learning-based software as medical device. *NPJ Digit Med*. 2020;**3**:53. doi:10.1038/s41746-020-0262-2
164. Mooghali M, Stroud AM, Yoo DW, *et al*. Trustworthy and ethical AI-enabled cardiovascular care: a rapid review. *BMC Med Inform Decis Mak*. 2024;**24**(1):247. doi:10.1186/s12911-024-02653-6
165. Ogg M, Coon WG. Self-supervised transformer model training for a sleep-EEG foundation model. *bioRxiv*. 2024. doi:10.1101/2024.01.18.576245
166. Mostafaei SH, Tanha J, Sharafkhaneh A. A novel deep learning model based on transformer and cross modality attention for classification of sleep stages. *J Biomed Inform*. 2024;**157**:104689. doi:10.1016/j.jbi.2024.104689
167. Chute CG. The rendering of human phenotype and rare diseases in ICD-11. *J Inherit Metab Dis*. 2018;**41**(3):563–569. doi:10.1007/s10545-018-0172-5
168. de Zambotti M, Goldstein C, Cook J, *et al*. State of the science and recommendations for using wearable technology in sleep and circadian research. *Sleep*. 2024;**47**(4). doi:10.1093/sleep/zsad325
169. Bandyopadhyay A, Oks M, Sun H, *et al*. Strengths, weaknesses, opportunities, and threats of using AI-enabled technology in sleep medicine: a commentary. *J Clin Sleep Med*. 2024;**20**(7):1183–1191. doi:10.5664/jcsm.11132
170. Willoughby AR, Golkashani HA, Ghorbani S, *et al*. Performance of wearable sleep trackers during nocturnal sleep and periods of simulated real-world smartphone use. *Sleep Health*. 2024;**10**(3):356–368.
171. Svensson T, Madhawa K, Nt H, Chung UI, Svensson AK. Validity and reliability of the Oura Ring Generation 3 (Gen3) with Oura sleep staging algorithm 2.0 (OSSA 2.0) when compared to multi-night ambulatory polysomnography: a validation study of 96 participants and 421,045 epochs. *Sleep Med*. 2024;**115**:251–263. doi:10.1016/j.sleep.2024.01.020
172. Neri L, Gallelli I, Dall'Olio M, *et al*. Validation of a new and straightforward algorithm to evaluate signal quality during ECG monitoring with wearable devices used in a clinical setting. *Bioengineering (Basel)*. 2024;**11**(3):222. doi:10.3390/bioengineering11030222
173. Geng D, Yin Y, Fu Z, *et al*. Heart rate detection method based on Ballistocardiogram signal of wearable device: algorithm development and validation. *Heliyon*. 2024;**10**(5):e27369. doi:10.1016/j.heliyon.2024.e27369
174. Fonseca P, Ross M, Cerny A, *et al*. A computationally efficient algorithm for wearable sleep staging in clinical populations. *Sci Rep*. 2023;**13**(1):9182. doi:10.1038/s41598-023-36444-2
175. Lee S, Small BJ, Cawthon PM, Stone KL, Almeida DM. Social activity diversity as a lifestyle factor to alleviate loneliness and chronic pain. *J Psychosom Res*. 2023;**172**:111434. doi:10.1016/j.jpsychores.2023.111434
176. Wallace ML, Lee S, Stone KL, *et al*. Actigraphy-derived sleep health profiles and mortality in older men and women. *Sleep*. 2022;**45**(4). doi:10.1093/sleep/zsac015
177. Lee S, Mu CX, Wallace ML, *et al*. Multidimensional sleep health problems across middle and older adulthood predict early mortality. *J Gerontol A Biol Sci Med Sci*. 2024;**79**(3):258.
178. Mirer AG, Young T, Palta M, Benca RM, Rasmuson A, Peppard PE. Sleep-disordered breathing and the menopausal transition among participants in the Sleep in Midlife Women Study. *Menopause*. 2017;**24**(2):157–162. doi:10.1097/GME.0000000000000744
179. Heinzer R, Marti-Soler H, Haba-Rubio J. Prevalence of sleep apnoea syndrome in the middle to old age general population. *Lancet Respir Med*. 2016;**4**(2):e5–e6. doi:10.1016/S2213-2600(16)00006-0
180. Eyre H, Alba PR, Gibson CJ, *et al*. Bridging information gaps in menopause status classification through natural language processing. *JAMIA Open*. 2024;**7**(1):ooae013. doi:10.1093/jamiaopen/ooae013
181. Shepertycky MR, Banno K, Kryger MH. Differences between men and women in the clinical presentation of patients diagnosed with obstructive sleep apnea syndrome. *Sleep*. 2005;**28**(3):309–314.
182. Wimms A, Woehrle H, Ketheeswaran S, Ramanan D, Armitstead J. Obstructive sleep apnea in women: specific issues and interventions. *Biomed Res Int*. 2016;**2016**:1764837. doi:10.1155/2016/1764837
183. Ye L, Pien GW, Weaver TE. Gender differences in the clinical manifestation of obstructive sleep apnea. *Sleep Med*. 2009;**10**(10):1075–1084. doi:10.1016/j.sleep.2009.02.006
184. Morris JL, Mazzotti DR, Gottlieb DJ, Hall MH. Sex differences within symptom subtypes of mild obstructive sleep apnea. *Sleep Med*. 2021;**84**:253–258. doi:10.1016/j.sleep.2021.06.001
185. Won CHJ, Reid M, Sofer T, *et al*. Sex differences in obstructive sleep apnea phenotypes, the multi-ethnic study of atherosclerosis. *Sleep*. 2020;**43**(5). doi:10.1093/sleep/zsz274
186. Hughes JM, Song Y, Fung CH, *et al*. Measuring sleep in vulnerable older adults: a comparison of subjective and objective sleep measures. *Clin Gerontol*. 2018;**41**(2):145–157. doi:10.1080/07317115.2017.1408734
187. Hisler GC, Muranovic D, Krizan Z. Changes in sleep difficulties among the U.S. population from 2013 to 2017: results from the National Health Interview Survey. *Sleep Health*. 2019;**5**(6):615–620. doi:10.1016/j.sleh.2019.08.008

188. Takahashi N, Matsumoto T, Nakatsuka Y, *et al.*; Nagahama Study Group. Differences between subjective and objective sleep duration according to actual sleep duration and sleep-disordered breathing: the Nagahama Study. *J Clin Sleep Med.* 2022;**18**(3):851–859. doi:10.5664/jcsm.9732
189. Pierson-Bartel R, Ujma PP. Objective sleep quality predicts subjective sleep ratings. *Sci Rep.* 2024;**14**(1):5943. doi:10.1038/s41598-024-56668-0
190. Pinsky MR, Bedoya A, Bihorac A, *et al*. Use of artificial intelligence in critical care: opportunities and obstacles. *Crit Care.* 2024;**28**(1):113. doi:10.1186/s13054-024-04860-z
191. Lotter W. Acquisition parameters influence AI recognition of race in chest x-rays and mitigating these factors reduces underdiagnosis bias. *Nat Commun.* 2024;**15**(1):7465. doi:10.1038/s41467-024-52003-3
192. Sengupta PP, Dey D, Davies RH, Duchateau N, Yanamala N. Challenges for augmenting intelligence in cardiac imaging. *Lancet Digit Health.* 2024;**6**:e739–e748. doi:10.1016/s2589-7500(24)00142-0
193. Polevikov S. Advancing AI in healthcare: a comprehensive review of best practices. *Clin Chim Acta.* 2023;**548**:117519. doi:10.1016/j.cca.2023.117519