communications medicine

Perspective

A Nature Portfolio journal

https://doi.org/10.1038/s43856-025-00886-8

Revealing sleep and pain reciprocity with wearables and machine learning

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Sleep disturbance and chronic pain share a bidirectional relationship with poor sleep exacerbating pain and pain disrupting sleep. Despite the substantial burden of sleep disturbance and pain, current treatments fail to address their interplay effectively, largely due to the lack of longitudinal data capturing their complex dynamics. Traditional sleep measurement methods that could be used to quantitate daily changes in sleep, such as polysomnography, are costly and unsuitable for large-scale studies in chronic pain populations. New wearable polysomnography devices combined with machine learning algorithms offer a scalable solution, enabling comprehensive, longitudinal analyses of sleep-pain dynamics. In this Perspective, we highlight how these technologies can overcome current limitations in sleep assessment to uncover mechanisms linking sleep and pain. These tools could transform our understanding of the sleep and pain relationship and guide the development of personalized, data-driven treatments.

Sleep disturbance affects more than one-third of the general population[1] and is associated with an increased risk of chronic illness and mortality[2]. Sleep disturbance is particularly prevalent among individuals with chronic pain[3,4], with estimates ranging from 67-88%. The bidirectional relationship between sleep and pain is well-documented: sleep disturbances exacerbate pain, while pain disrupts sleep[5–9]. Poor sleep intensifies pain, fatigue, psychiatric comorbidities, and disability[3,10–12]. Conversely, acute and chronic pain interferes with sleep onset, maintenance, quality, and duration[13,14].

Despite the recognition of this vicious cycle, current treatments are not optimized to address the interplay between sleep and pain. While psychological interventions such as Cognitive Behavioral Therapy for Insomnia (CBT-I)[15] and CBT for Chronic Pain (CBT-P)[16] primarily target sleep disturbance and pain, respectively, both have demonstrated benefits on secondary outcomes (i.e., CBT-I improving pain and CBT-P improving sleep)[17,18]. However, it remains unclear which treatment components are most effective for whom and when. Research suggests that combined approaches (i.e., CBT-I/P) that simultaneously target both sleep disturbance and pain may be more effective[17]. However, these treatments have yet to be optimized to address the bidirectional relationship between sleep and pain[18]. This leaves a significant gap in pain management strategies and a missed opportunity to improve patient outcomes. Moreover, while the reciprocal nature of this relationship is widely acknowledged, our understanding of the underlying mechanisms remains incomplete. In particular, a comprehensive understanding of the causal associations between objective sleep measures and pain variables is lacking[5,7,19,20].

The absence of longitudinal, high-quality sleep data has been a major barrier to uncovering the dynamics between sleep and pain. Traditional objective sleep measurement methods, such as polysomnography (PSG, see Fig. 1 for an overview of sleep measurement methods), which is the gold-standard for assessing sleep and diagnosing sleep disorders, are costly, inconvenient, and often unsuitable for large-scale or long-term studies. Worse, some traditional inferential sleep measurements, such as actigraphy, can be inaccurate in the chronic pain population[21–24]. Similarly, movement- and heart rate-based contactless devices, including pressure sensors, piezoelectric sensors, bedside radiofrequency sensors, and infrared cameras, cannot detect sleep stages or accurately differentiate wake from sleep in individuals with chronic pain, particularly when movement disturbances or altered physiological responses affect signal interpretation[25]. Furthermore, the vast amount of data generated by these devices each night, which are in the gigabyte range for PSG, combined with the complex, likely non-linear interaction between sleep and pain variables, present significant challenges for traditional statistical methods, which typically assume linear relationships[26,27].

Recent advances in wearable PSG devices and machine learning present a promising avenue for addressing these challenges[28–35]. Wearable PSG devices enable the collection of objective sleep data in naturalistic settings, while machine learning algorithms excel at identifying patterns and correlations within large, complex datasets. In this Perspective, we advocate for wearable PSG devices as an accurate, convenient, scalable, and affordable measure of objective sleep in the chronic pain population. As these devices

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	Lab-based PSG	Actigraphy	Wearable PSG
In Use			
Accuracy	Criterion standard for objective sleep measures; uses multiple electrodes and sensors	High sensitivity for detecting sleep (>90%) but low specificity for detecting (20-70%)	Measures brain activity achieving >80% accuracy compared to lab-based PSG
What it measures	Brain activity, eye and muscle movement, heart electrical activity, breathing (EEG, EMG, EOG, ECG, respiratory signals)	Movement (accelerometer) and heart rate	Brain activity, movement, heart rate, position (EEG, accelerometer, gyroscope, heart rate)
Recording Setting	In a sleep lab with a trained technician	Home-based; user-administered	Home-based; user-administered
Cost	Expensive	Affordable	Affordable
Data Output	Comprehensive sleep architecture, physiological data, suitable for diagnosing sleep disorders	Binary sleep or wake	Similar to lab-based but from non-traditional electrode locations

Fig. 1 | Sleep recording modalities: Lab-Based PSG, actigraphy, and wearable PSG devices. This figure summarizes key features of lab-based PSG, actigraphy, and wearable PSG across several domains, including accuracy, signal types, recording setting, convenience, cost, and data output. Electroencephalogram (EEG) measures brain activity, electrooculogram (EOG) measures eye movements, electromyogram (EMG) measures muscle activity, electrocardiogram (ECG) measures heart electrical activity, accelerometer measures linear movements, and gyroscope measures rotational motion.

can be employed at home with limited training, we argue that they have the potential to yield large quantities of accurate objective sleep data. Together with machine learning algorithms, wearable PSG devices offer a powerful opportunity to elucidate the reciprocal relationship between sleep and pain, opening new pathways for treatment optimization.

Bidirectional Relationship Between Sleep and Pain

Sleep consists of two distinct stages: non-rapid eye movement (NREM) and rapid eye movement (REM) sleep[36]. NREM is further categorized into three stages (N1, N2, N3) progressing from light to deep sleep[37]. Sleep typically cycles through these stages in approximately 90-minute intervals accompanied by a brief arousal at the end of the cycle. There is a gradual shift from predominantly NREM (N1 to N2 to N3) early in the night to REM-dominated cycles later. Sleep stages can be quantified by the frequency and amplitude of electrical activity in the brain, which can be assessed by electroencephalogram (EEG).

The reciprocal relationship between sleep and pain is well-documented in human and animal studies[38,39]. Individuals with chronic pain often report disrupted sleep (e.g., decreased total sleep time, increased sleep onset latency, increased wakefulness after sleep onset, increased number of awakenings) due to pain. For example, many individuals with chronic pain have delayed sleep onset because of difficulty finding comfortable positions to fall asleep[13]. They also report difficulty staying asleep because of frequent awakenings due to painful stimuli and challenges falling back asleep[13,14]. Sleep disruption caused by pain can lead to sleep fragmentation and alter the time spent in distinct sleep stages. For example, individuals with fibromyalgia-related chronic pain tend to experience an increased number of awakenings and more N1 and N2 sleep (light sleep) compared to normative data[19,40]. Additionally, pain can disrupt deep sleep (N3) leading to fragmented N3 and potentially reduced functional efficiency in this stage[38,39]. Similarly, individuals with rheumatoid arthritis tend to experience more alpha and less theta or delta brain activity during NREM sleep stages, indicating lighter NREM[41]. The increased lighter sleep stage and decreased deep sleep stage may be associated with unrefreshing sleep and fatigue the following day. Indeed, many individuals with fibromyalgia and rheumatoid arthritis report fatigue, nighttime arousal due to pain, and morning stiffness[40,41]. Furthermore, other factors such as mental health (e.g., depression, anxiety, post-traumatic symptoms)[42–44] and medications (e.g., opioids)[45,46] can also impact sleep disturbances.

Conversely, sleep disturbances exacerbate pain. Sleep deprivation can alter one's pain perception by increasing pain sensitivity and hindering pain modulation[12,47]. Experimental studies have found that sleep loss from delayed sleep onset can result in next-day sensitivity to heat and pressure pain, whereas sleep loss from frequent awakenings can result in next-day sensitivity to cold pain[48,49]. These findings suggest that the type of sleep loss can impact pain sensitivity. It is also notable that sleep disturbances have a more pronounced effect on pain than pain has on sleep[7,9,10,50,51]. Likewise, cumulative sleep loss, regardless of its cause, can increase one's pain sensitivity, interrupt the restorative function of sleep, and result in prolonged healing processes[8]. In particular, cumulative sleep loss and disruptions in deep sleep state can lead to decreased immune function[52–54], memory/learning ability[55], and metabolic waste clearance[56,57]. Additionally, ongoing disruption of REM sleep has also been suggested to promote attention to pain sensations, amplify catastrophizing, and reduce distraction analgesia via the mesolimbic system[39].

Despite substantial progress in understanding the sleep-pain relationship, significant gaps remain. Key questions include which types of sleep disruptions are most detrimental to pain and how these disruptions impact cognitive, emotional, and physical functioning[19]. For instance, do interruptions during specific sleep stages carry greater consequences than general sleep fragmentation and if so, for which types of pain? Similarly, the extent to which pain characteristics (e.g., location, intensity, duration) influence sleep stages remains unclear. Furthermore, the variable nature of both sleep and pain complicates the detection of consistent patterns, particularly in studies relying on single-night recordings from small cohorts. An individual's history of pain or sleep disturbance may also shape their current physical and psychological state, further complicating analyses[5,7]. It is possible that an individual's history of pain or sleep disturbance can significantly influence or even predict their current physical or psychological state, including anxiety and catastrophizing. Likewise, given that sleep and pain interactions vary across age[58], gender[59,60], race[60,61], and socioeconomic status[62], it is reasonable to surmise that answers to the questions above can depend on these demographic and socioeconomic factors. Answering questions like these is critical as doing so could help identify potential mediators and moderators of the sleep-pain interplay, ultimately guiding more targeted and effective treatments.

Machine Learning and the Limitations of Traditional Measures of Objective Sleep

Machine learning can be a powerful tool for uncovering complex relationships between sleep and pain. Machine learning algorithms excel at classifying, categorizing, and clustering data, and identifying patterns and correlations that might otherwise be obscured by noise[63,64]. In recent years, machine learning has seen widespread adoption in medicine[28], with applications ranging from diagnosing issues such as sleep apnea[29,65,66] and mental health disorders[30] to interpreting medical images[31,32], designing personalized treatment plans[33,34], and promoting behavioral changes[35]. Notably, machine learning analyses have identified sleep disturbances as a core factor in chronic pain's most severe presentations[67].

The proliferation of machine learning has been driven by advances in algorithms, the accessibility of affordable computing power, and the availability of large, low-cost datasets. Indeed, large datasets are often essential for training machine learning algorithms[68]. Within the context of sleep and pain, machine learning algorithms thrive on large and detailed datasets that include both subjective and objective measures. Objective sleep data, in particular, are invaluable, as they often contain richer and more detailed information than subjective self-reports. For instance, a single night of objective sleep data can provide continuous, real-time recordings from multiple physiological signals, enabling deeper insights into the dynamics between sleep and pain. Therefore, employing machine learning to study the bidirectional relationship between sleep and pain benefits from the ability to acquire longitudinal objective sleep data.

Traditional methods of objective sleep measurement (Fig. 1), such as PSG, provide comprehensive data, including summative measures of sleep and wake (e.g., total sleep time, wake after sleep onset), sleep architecture (e.g., NREM and REM durations), and electrophysiological signals (e.g., EEG power spectra). However, traditional PSG requires a laboratory setting and trained technicians, making it costly and inconvenient for patients. These logistical challenges limit its feasibility for large-scale or longitudinal studies, resulting in small sample sizes and brief, typically single night recording durations. Portable PSG systems enable comprehensive sleep studies outside of traditional labs, including at a person's home[69]. They provide physiological data comparable to in-lab PSG whilst being more accessible and enabling the person being monitored to be more comfortable. However, they often require a trained technician for setup and application of electrodes, limiting their practicality for longitudinal data collection. Additionally, while portable, these systems can be bulky, potentially impacting compliance or mobility.

While research-grade wearable devices have been used in sleep research for nearly 40 years, the recent proliferation of consumer-grade wearable devices that impute sleep have opened new avenues into longitudinal sleep recordings, as these devices are relatively inexpensive and easy for people to use at home. The most widely used wearable devices for sleep measurement use wrist worn accelerometers ('actigraphs'), sometimes in combination with heart rate and heart rate variability measurements, to impute sleep state. Actigraphs infer sleep continuity based on the assumption of sleep during a specific time frame and determine when sufficient movement indicates a likely awakening from sleep[22]. These devices typically have a high sensitivity for detecting sleep (> 90%) but a low specificity for detecting wakefulness (20–70%)[21]. Therefore, these devices can be quite accurate for good sleepers, who have relatively little wake after sleep onset and spend relatively little time in bed before falling asleep. However, actigraphs can yield highly misleading information in individuals who sleep poorly, especially in those with extended awakenings at night or those who spend a long time in bed prior to sleep onset, for which these devices would interpret wakeful periods with little movement as sleep. Therefore, the utility of actigraphs in recording longitudinal sleep patterns in those with chronic pain, in whom such periods of pre- and mid-sleep wakefulness is common, is of dubious value.

Using wearable PSG Devices

More recently, wearable PSG devices (e.g., Sleep Profiler, Zmachine, Dreem, MUSE) have entered the market[70]. Wearable PSG devices typically include multiple sensors, including an EEG sensor for brain waves, accelerometers for movement, gyroscopes for orientation, and heart rate monitors. Wearable PSG devices, therefore, measure many of the same physiological signals as lab-based PSG. Indeed, data from wearable PSG devices can be used to assess detailed sleep information, including sleep continuity, sleep stages, and the power spectrum of EEG signals with similar accuracy (>80%) as lab-based PSG[71–75]. Studies have also reported that wearable PSG devices provide sleep continuity data with significantly better agreement with laboratory PSG than actigraphy-derived sleep data[76,77]. This is a reasonable expectation since wearable PSG devices directly measure brain activity, whereas actigraphs can only infer sleep from gross movement.

Wearable PSG devices are also accurate in determining the occurrence and duration of midsleep awakenings[76], which can occur because of pain. Likewise, given that, as discussed above, sleep stage information derived from lab-based PSG can be influenced by pain, it is reasonable to expect similar findings with data from wearable PSG devices. Finally, wearable PSG devices' affordability, combined with their ease of use at home, naturally facilitates the collection of large datasets consisting of sleep data from many nights.

Wearable PSG devices do have drawbacks, including the use of fewer channels or leads than lab-based PSG, which may reduce the accuracy of sleep measurements in those with pathological sleep. Additionally, because home-based recordings lack real-time technician monitoring, signal artifacts may occur due to incorrect device use, Bluetooth or internet connection instability, or variability in how users wear headband devices. Factors such as improper fit, shifting during sleep, or discomfort leading to device removal can also compromise data quality by causing signal loss, temporary disconnections, or unintended recording interruptions. Sensitivity and specificity may also vary across devices, as different developers utilize distinct software algorithms.

Large data sets, derived from repeated measurements over time, can ameliorate the effects of sleep and pain variability, improve signal-to-noise ratios, and naturally lend themselves to analyses by machine learning. Indeed, the EEG data alone recorded by wearable PSG can amount to several gigabytes per week. Because of the accuracy, low burden, comprehensive set of recording modalities, and ability to produce large datasets, wearable PSG devices are a powerful tool for measuring objective sleep and a nearly ideal match for studies employing machine learning algorithms to uncover the mechanisms behind the bidirectional relationship between sleep and pain and to identify potent treatment mediators and moderators. In addition to physiological data, self-reported measures, such as sleep diaries, pain intensity ratings, and psychological and behavioral factors (e.g., stress, mood, catastrophizing, activity level), provide valuable information for understanding this complex interplay. The integration of these multimodal data streams with machine learning can enhance our ability to identify distinct sleep-pain phenotypes, individual variability, and key risk and protective factors, thereby optimizing treatment selection.

With these insights, digital health solutions can facilitate personalized treatments tailored to individual sleep and pain profiles rather than relying on one-size-fits-all approaches. For example, if nighttime hyperarousal is detected, insights from machine learning can determine whether biofeedback, mindfulness, or relaxation exercise is most effective for an individual's specific sleep-pain profile. If pain catastrophizing is contributing to emotional distress and sleep disruption at night, cognitive restructuring (e.g., challenging and replacing unhelpful thoughts), emotional regulation exercise (e.g., journaling, self-compassion exercises), and relaxation techniques can be prioritized. If sedentary behavior contributes to worsening pain and sleep, personalized physical activity or pacing strategies can help mitigate pain-related deconditioning. If persistent poor sleep efficiency due to delayed sleep onset is identified, machine learning algorithms can adjust sleep restriction therapy or stimulus control based on multi-night sleep feedback. These are just a few examples of how personalized interventions can be tailored based on individual's unique sleep-pain cycle. Such adaptive approaches can optimize real-time treatment strategies, ensuring that interventions are delivered at the right time, for the right person, and with the right strategy.

Future Directions and Conclusions

The interplay between sleep disturbance and chronic pain presents a critical challenge for both research and clinical care. The recent advances in wearable PSG devices and machine learning algorithms provide a unique opportunity to deepen our understanding of this complex bidirectional relationship. Wearable PSG devices offer an affordable, scalable, and accurate solution for longitudinal data collection, while machine learning excels at uncovering patterns and correlations within large, complex datasets. Together, these tools have the potential to revolutionize how we study and address the reciprocal effects of sleep and pain.

The combination of wearable PSG devices and machine learning can also be potent for enabling personalized and optimized digital interventions for sleep and pain. Such a digital intervention could conceivably be based on machine learning algorithms trained on crowdsourced data from both wearable PSGs and surveys from smartphone-based apps. With a trained machine learning algorithm at hand, each user's optimized treatment program could then be automatically generated from their sleep and pain data and updated over time as necessary to reflect changes in their lifestyle or needs. These treatments can potentially advance sleep and pain medicine by enabling the development of personalized interventions with precise real-time monitoring. Digital interventions can also ameliorate logistical and financial barriers by improving treatment access for the broader population, including those with lower socioeconomic status or those living in rural areas.

In conclusion, the convergence of wearable technology and machine learning can represent a transformative frontier in sleep and pain research. By embracing these innovations, we can potentially move toward a future where interventions are more effective, personalized, and widely accessible. Addressing the intertwined challenges of sleep and pain has the potential to improve the quality of life for millions of individuals worldwide.

Received: 14 December 2024; Accepted: 29 April 2025;
Published online: 07 May 2025

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Acknowledgements
We acknowledge funding from NIH T32 DA035165 (SK), NIH K24 DA053564 (BDD), and K24NS126781 (SM).

Author contributions
S.K. conceived the article and prepared the first draft and subsequent revisions with input from J.M.Z., S.M. and B.D.D.; All co-authors critically reviewed the manuscript, including all revisions, and agreed on the final version for submission to the journal. S.M. and B.D.D. contributed equally as co-senior authors.

Competing interests
The authors declare no competing interests.

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Peer review information *Communications Medicine* thanks the anonymous reviewers for their contribution to the peer review of this work.

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