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Wearable sensors and artificial intelligence for sleep monitoring
Applications in recovery and health management

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Wearable sensors offer non-invasive, continuous health monitoring and are rapidly transforming clinical exercise physiology. Sleep, a cornerstone of physiological recovery, remains under-assessed in outpatient care, despite its impact on adaptation, cardiovascular function, metabolic regulation, and immune restoration. This review explores the role of wearable technologies –such as smartwatches, rings, headbands, chest straps, and smart textiles– in tracking sleep architecture, heart rate variability (HRV), respiratory metrics, and circadian rhythms in real-world conditions. Devices integrating photoplethysmography, accelerometry, electrocardiography (ECG), and electroencephalogram (EEG) increasingly provide accurate and ecologically valid insights into recovery dynamics. Artificial intelligence (AI) enhances the clinical potential of these wearables by enabling real-time, individualized feedback and predictive modeling. Applications include recovery monitoring in cardiac and pulmonary rehabilitation, early detection of sleep-disordered breathing, assessment of post-COVID fatigue, and identification of neurodegenerative risk through changes in sleep patterns. In older adults and those with metabolic disorders, sleep-derived metrics such as reduced deep sleep or altered HRV provide actionable data for tailoring exercise prescriptions and detecting maladaptive responses. However, limitations still remain. Many devices lack validation against gold-standard polysomnography, and proprietary algorithms limit clinical transparency. Integration into electronic health records and routine workflows is still uncommon. Moreover, issues of digital access, data privacy, and algorithmic bias pose ethical and practical challenges, particularly in underserved populations. Despite these barriers, wearable sleep monitoring presents a promising frontier in recovery science. By combining biosignal analysis with AI-driven interpretation, these technologies enable a shift from passive data collection to active, personalized health management. Future research should prioritize standardized validation across diverse populations, open-source algorithm development, and equitable deployment. Ultimately, sleep metrics –when integrated thoughtfully– can serve as critical biomarkers of readiness and recovery, empowering clinicians and patients alike in optimizing health outcomes.

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1. INTRODUCTION

Sleep is a fundamental physiological process, essential for tissue repair, memory consolidation, immune regulation, and cardiovascular stability. Its disruption is increasingly recognized as a modifiable risk factor in the development and progression of chronic diseases such as heart failure, diabetes, and neurodegenerative disorders.[1] Clinical populations –particularly older adults and individuals in rehabilitation– are disproportionately affected by sleep disturbances, which impair recovery, elevate fatigue, and worsen clinical outcomes.

Polysomnography (PSG) remains the gold standard for diagnosing sleep disorders and assessing architecture; yet it is constrained by high cost, limited accessibility, and

poor ecological validity.[1,2] Moreover, the artificial sleep environment and multi-sensor setups often compromise the authenticity of observed patterns. To address these challenges, wearable technologies have rapidly emerged as powerful tools for unobtrusive, real-time monitoring of sleep and recovery in free-living conditions.

Modern wearable devices, ranging from wristbands and smart rings to textile sensors and electroencephalogram (EEG) headbands, collect a wide array of biosignals, such as heart rate variability (HRV), respiration, temperature, actigraphy, and oxygen saturation.[3–5] These data-rich platforms enable longitudinal assessments of sleep quality and recovery dynamics, with applications extending into hydration tracking and metabolic profiling.[6,7]

Crucially, the integration of artificial intelligence (AI) has revolutionized the potential of wearable systems. Machine learning algorithms now enhance the accuracy of sleep staging, detect anomalies such as apnea, and support adaptive feedback based on individualized sleep-wake profiles. These advancements have made wearables not only more clinically relevant but also transformative in the field of clinical exercise physiology, where real-time insight into recovery, autonomic function, and circadian alignment is essential.[8] While challenges remain —including algorithm transparency, sensor variability, and digital equity— the convergence of wearable biosensing, AI analytics, and cloud-based platforms is driving a paradigm shift. Wearable sleep monitoring is evolving from a passive observational tool into an active agent of personalized care and predictive rehabilitation.

2. ARTIFICIAL INTELLIGENCE IN WEARABLE SLEEP MONITORING

AI has emerged as a transformative force in the analysis and application of wearable sleep data. Through machine learning and deep learning algorithms, AI enhances the accuracy of sleep stage classification, detection of sleep-disordered breathing, and prediction of recovery outcomes. These algorithms can integrate multiple biosignals —such as HRV, EEG, and actigraphy— while learning individual user patterns, enabling more personalized insights. AI-enabled platforms like Dreem and Oura use proprietary models to refine sleep architecture estimation, while open-source approaches are advancing transparency and reproducibility in clinical contexts.[9,10]

Beyond descriptive analytics, AI supports predictive modeling for adverse events (e.g., sleep apnea, overtraining) and guides adaptive feedback through mobile applications. Natural language processing and explainable AI are also being integrated to improve clinician-patient interaction with wearable data. As AI algorithms evolve, they hold the potential to transform passive monitoring into interactive, real-time health coaching tools, redefining recovery management in clinical exercise physiology.

3. PHYSIOLOGY OF SLEEP AND ITS ROLE IN CLINICAL RECOVERY

Sleep is not a passive state but an active, cyclical biological process characterized by dynamic changes in brain activity, autonomic tone, metabolic regulation, and musculoskeletal restoration.[1] It is classically divided into non-rapid eye movement (NREM) sleep —comprising stages N1 to N3— and rapid eye movement (REM) sleep. These stages cycle approximately every 90 minutes and are distinguishable by electrophysiological and cardiorespiratory features.[1,2]

During deep NREM sleep (N3), parasympathetic activity predominates, leading to reductions in heart rate, blood pressure, sympathetic outflow, and metabolic rate, creating an optimal environment for cellular repair, immune recovery, and hormonal regulation.[4,5] In contrast, REM sleep exhibits irregular autonomic fluctuations and increased cerebral metabolism, supporting memory consolidation and emotional regulation.[8,11] Recent findings further demonstrate that better sleep quality, in conjunction with higher physical activity levels, is linked to reduced emotion dysregulation in individuals with major depressive disorder, highlighting the psychological benefits of integrated behavioral interventions.[11]

3.1. Consequences of sleep disruption in clinical populations

The role of sleep in clinical recovery is increasingly recognized across diverse patient populations. In individuals with cardiovascular disease, sleep restriction or fragmentation is associated with elevated sympathetic tone and reduced HRV, which are predictive of adverse outcomes.[4,5] In metabolic disease, short or poor-quality sleep exacerbates insulin resistance, systemic inflammation, and appetite dysregulation, undermining recovery trajectories.[3] From a clinical exercise physiology perspective, sleep provides critical physiological substrates for adaptation to training and rehabilitation stimuli. Studies have shown that adequate sleep enhances exercise-induced gains in mitochondrial function, muscle protein synthesis, and neuromuscular coordination, mechanisms essential in restoring function after injury or illness.[10] In contrast, sleep deprivation impairs

exercise tolerance, increases perceived exertion, and delays post-exercise recovery.[2]

HRV has emerged as a non-invasive, surrogate biomarker of recovery and autonomic balance, and it is now frequently measured via wearable sensors in both research and clinical contexts.[4,5,9] Longitudinal HRV monitoring during sleep allows clinicians to assess recovery capacity in patients undergoing cardiac or pulmonary rehabilitation, with deviations from baseline often indicating poor sleep, stress, or maladaptive physiological responses.[8] Emerging data also highlight the relationship between sleep and neurodegenerative disease progression. Altered REM-NREM cycling, sleep fragmentation, and reduced slow-wave activity have been observed in early Alzheimer's and Parkinson's disease, suggesting that sleep abnormalities may serve as early clinical biomarkers.[1] Wearable sleep monitoring could thus provide actionable insights not only into recovery but also into long-term neurological risk stratification.

In sum, sleep quality is integrally linked with recovery outcomes across clinical conditions. Understanding sleep physiology –and leveraging wearable sensors to quantify it– offers a powerful tool for enhancing the personalization of therapeutic exercise and recovery plans.

4. TECHNOLOGIES IN WEARABLE SLEEP MONITORING

The field of wearable sleep technology has evolved rapidly, transitioning from basic actigraphy devices to advanced, multi-sensor systems, capable of estimating sleep stages, detecting sleep disorders, and assessing physiological recovery markers in real time. These tools are especially valuable for clinical populations, where continuous and unobtrusive monitoring can inform rehabilitation, track disease progression, and personalize care strategies.[1,8]

4.1. Types of wearable technologies

Wearable devices used for sleep monitoring vary significantly in both form factor and sensor configuration, offering a range of options tailored to different user needs and clinical contexts. Among the most common are *wrist-worn devices*, such as the Fitbit, Garmin, and Xiaomi Smart Band 9. These typically employ photoplethysmography (PPG) to monitor peripheral blood flow and accelerometers to detect movement. Some models also incorporate electrodermal activity sensors to estimate sleep-wake cycles and total sleep duration.[3]

Smart rings, including the Oura Ring 4 and Samsung Galaxy Ring, represent a compact and user-friendly alternative. These devices integrate PPG for pulse detection, skin temperature sensors, and actigraphy to estimate sleep stages. In addition, they track HRV, a key marker of autonomic nervous system balance and physiological recovery, providing deeper insight into the user's readiness and overall health status.

Chest-worn straps and adhesive patches, such as the Zephyr BioHarness, focus on collecting electrocardiograph (ECG)-derived HRV and respiratory rate metrics. These devices are particularly suited for scenarios requiring high-fidelity cardiovascular and respiratory monitoring, such as during rehabilitation or in athletic performance contexts.

Headbands and eye masks, including devices like Dreem and Muse S, enable direct assessment of brain and ocular activity through EEG and electrooculography (EOG) recordings. As such, they offer enhanced accuracy in sleep staging and can serve as practical alternatives to traditional polysomnography in certain clinical or research settings.

Lastly, smart textiles and adhesive biosensor patches represent an emerging class of wearables designed for continuous, unobtrusive monitoring. These technologies allow for real-time tracking of cardiorespiratory and postural data without compromising sleep comfort, making them ideal for long-term use in naturalistic environments.

Wearable systems may be classified as single-sensor (e.g., standalone pulse oximeters) or multi-sensor platforms that combine accelerometry, HRV, SpO_2, skin temperature, and other physiological signals. Multi-sensor wearables are particularly valuable in clinical recovery settings due to their capacity for integrative assessment. Table 1 provides a comparative overview of representative devices, detailing their sensor types, clinical applications, and the extent of AI integration across target populations.

4.2. Validity and comparison to polysomnography

Polysomnography (PSG) remains the gold standard for sleep assessment; however, its clinical use is limited by infrastructure, cost, and patient burden. Numerous validation studies have shown that modern wearables can approximate sleep duration and efficiency with reasonable accuracy, especially under free-living conditions.[1,2] For example, home-based portable PSG setups with reduced sensor arrays are now feasible alternatives, supported by AI-driven analysis algorithms.[12] Accuracy varies widely by device and outcome variable. For instance, total sleep time and sleep efficiency tend to be well estimated, while sleep staging and awakenings remain challenging to detect with high sensitivity. Devices like Whoop 4.0, Oura Ring 4, and

Table 1. Overview of wearable devices used in sleep monitoring and recovery applications. This table summarizes representative wearable technologies, their integrated sensors, target clinical populations, typical use cases in recovery and rehabilitation, and the degree of artificial intelligence (AI) integration. Devices are selected based on recent literature and current clinical or commercial relevance.

Device type/example	Sensors	Target population	Clinical use	AI integration	Reference
Oura Ring 4	PPG, Temp, HRV, accelerometer	Cardiac rehabilitation, older adults	Sleep staging, recovery readiness	Yes (proprietary ML)	Belabbaci & Alam[6]
Whoop Band	PPG, HRV, accelerometer	Cardiac, post-COVID	HRV tracking, fatigue management	Yes	Handy et al[8]
Dreem Headband	EEG, EOG, accelerometer	Neurodegenerative risk	Sleep stage estimation, REM analysis	Yes (EEG-based AI)	Vitazkova et al[1]
Fitbit/Garmin Watch	PPG, accelerometer, SpO_2	Metabolic disorders, T2DM	Sleep tracking, HRV, activity rhythm	Basic	Kazansky et al[3]
Withings BeamO	ECG, temperature, SpO_2, radar	General, post-discharge	Home diagnostics, REM/circadian	Emerging	Withings[14]
Zephyr BioHarness	ECG, respiration, HRV	Rehabilitation monitoring	Autonomic tracking, fitness recovery	No	Li et al[4,5]

PPG: Photoplethysmography, HRV: Heart rate variability, EEG: Electroencephalography, EOG: Electrooculography, T2DM: Type 2 diabetes mellitus

Dreem have shown improved performance in estimating REM and deep sleep stages through machine-learning-enhanced algorithms.[6,9]

4.3. Remote monitoring and clinical utility

Wearable data can now be transmitted securely to cloud platforms, enabling remote sleep assessments, integration with electronic health records, and alerts for sleep disruptions or recovery delays. In clinical exercise physiology, this enables longitudinal tracking of recovery from injury, surgery, or chronic conditions such as chronic obstructive pulmonary disease (COPD) or heart failure.[13] Emerging solutions such as the Withings BeamO, a multi-sensor remote scanner, and the Patchkeeper wearable stethoscope, are expanding the physiological scope of at-home monitoring to include respiratory sounds, ECG, and temperature, enabling richer sleep and recovery profiling.[14,15]

Importantly, several studies suggest that combining wearable-derived sleep data with HRV and circadian rhythm metrics provides a more complete picture of physiological recovery. This is particularly valuable in post-hospital discharge, post-COVID, or cardiac rehabilitation settings where subtle deviations in sleep patterns may precede overt symptoms.[3,8]

5. CLINICAL APPLICATIONS

The integration of wearable sleep monitoring into clinical practice has opened new pathways for personalized health management, especially in populations requiring structured recovery interventions. In clinical exercise physiology, where the optimization of recovery, adaptation, and function is central, wearables provide a dynamic means of assessing physiological readiness and response across diverse pathologies.

5.1. Recovery monitoring in cardiovascular and pulmonary rehabilitation

Wearable sensors provide valuable early indicators of autonomic imbalance and suboptimal recovery in patients undergoing cardiac or pulmonary rehabilitation. Research shows that decreased sleep efficiency or altered HRV –a key measure of autonomic nervous system function– during sleep is associated with poor cardiovascular outcomes and increased readmission risk.[4,5] Figure 1 illustrates a clinical case example where wearable-derived sleep and HRV data guided post-myocardial infarction (MI) rehabilitation decisions. For example, declines in deep sleep (N3)

Case Vignette: Post-Cardiac Rehabilitation Monitoring	
Parameter	**Observation**
Age/Sex	67/male
Diagnosis	Recent MI, T2DM
Intervention	Oura Ring – sleep/HRV tracking
Recorded Changes	↓ HRV, ↓ deep sleep, ↑ glucose
Outcome	↑ HRV, ↑ sleep quality, improved glucose

Figure 1. Case example of wearable sleep monitoring in post-cardiac rehabilitation. This infographic illustrates the application of a wearable device (e.g., Oura Ring 4 or Whoop 4.0) for tracking physiological metrics, and responsive clinical decisions in a patient. HRV: Heart rate variability, MI: Myocardial infarction, T2DM: Type 2 diabetes mellitus.

coupled with low nocturnal HRV prompted adjustments to exercise intensity, mitigating overtraining risks. Advanced wearable devices like the Whoop 4.0 and Oura Ring enable clinicians to monitor these critical recovery markers in real time, tracking: Nocturnal HRV patterns (autonomic recovery), resting heart rate trends (cardiovascular strain) and respiratory rate variations (early signs of pulmonary compromise). This continuous physiological data offers unprecedented insight into patient recovery trajectories, allowing for timely clinical interventions when needed.

5.2. Sleep disturbances in metabolic disorders and post-COVID fatigue

Patients with metabolic syndromes, including type 2 diabetes and obesity, demonstrate characteristic sleep disturbances that exacerbate insulin resistance and systemic inflammation.[3] Advanced wearable monitoring now enables clinicians to correlate specific sleep architecture abnormalities (particularly reduced deep sleep and REM) with glycemic variability and fatigue severity. Emerging applications extend to hydration monitoring,[16] where nocturnal polyuria risk assessment complements traditional sleep metrics. In parallel, post-COVID syndrome research utilizing these devices reveals persistent circadian dysregulation and sleep fragmentation,[1] with reduced REM sleep emerging as a particularly robust biomarker for both metabolic and post-viral recovery trajectories.

5.3. Neurological risk screening and early detection

Changes in sleep parameters such as REM sleep behavior, sleep fragmentation, or circadian rhythm variability may serve as early indicators of neurodegenerative conditions such as Parkinson's and Alzheimer's disease.[1] Continuous home-based monitoring with wearable EEG bands, HRV trackers, or multi-sensor headbands facilitates early screening, especially in high-risk populations. Devices like Dreem, Muse S, and novel radar-based monitors (e.g., BeamO) offer non-invasive, longitudinal data useful in neurocognitive rehabilitation.

5.4. Applications in older adults and frailty prevention

Older adults often experience fragmented sleep and diminished restorative sleep stages, contributing to frailty, reduced exercise tolerance, and fall risk. Wearables like smart rings, wristbands, and smart textiles provide an opportunity to track not only sleep, but also overnight HRV and mobility indicators, which can be integrated into fall risk prediction models or frailty assessments.[8,17] Combined with telemonitoring platforms, these devices facilitate aging-in-place models with real-time feedback loops between patients and care teams.

5.5. Feedback-driven rehabilitation and remote coaching

Wearables now offer patients access to self-regulated sleep hygiene strategies via feedback apps. Platforms such as Whoop, Oura, and Garmin Connect integrate sleep scores, readiness indices, and recovery trends that can guide behavioral interventions and exercise scheduling. For example, decreased HRV or low sleep efficiency may trigger automatic adjustments to training loads or rehabilitation exercises, enabling more individualized pacing during clinical recovery.[9]

6. INTEGRATION WITH CLINICAL EXERCISE PHYSIOLOGY

Clinical exercise physiology is grounded in the use of structured physical activity to improve function, health outcomes, and quality of life in individuals with chronic disease or functional limitations. Sleep (particularly its quality, architecture, and circadian alignment) plays a central role in modulating the effectiveness of exercise-based interventions. The integration of wearable sleep monitoring into this field offers new precision in tailoring exercise prescriptions, evaluating recovery, and detecting maladaptation early. Figure 2 illustrates how AI supports clinical decision-making by extracting meaningful patterns from sleep biosignals, bridging wearable technology with personalized recovery planning.

6.1. Sleep and physiological readiness

Recovery is not merely the absence of symptoms, but also reflects systemic readiness to adapt to a physiological load. Sleep, especially deep NREM stages, supports muscle repair, hormonal regulation, immune rebalancing, and autonomic recalibration.[1,4] Wearables that measure HRV, resting heart rate (RHR), and sleep stage distribution (e.g., Oura Ring, Whoop Band, Garmin) provide real-time insights into recovery status, allowing exercise physiologists to adjust workloads dynamically based on data rather than fixed timelines.

For instance, a patient with low HRV and reduced deep sleep post-exercise may benefit from a lighter training day, prioritizing mobility or active recovery, rather than progressing intensity. Conversely, high HRV and efficient

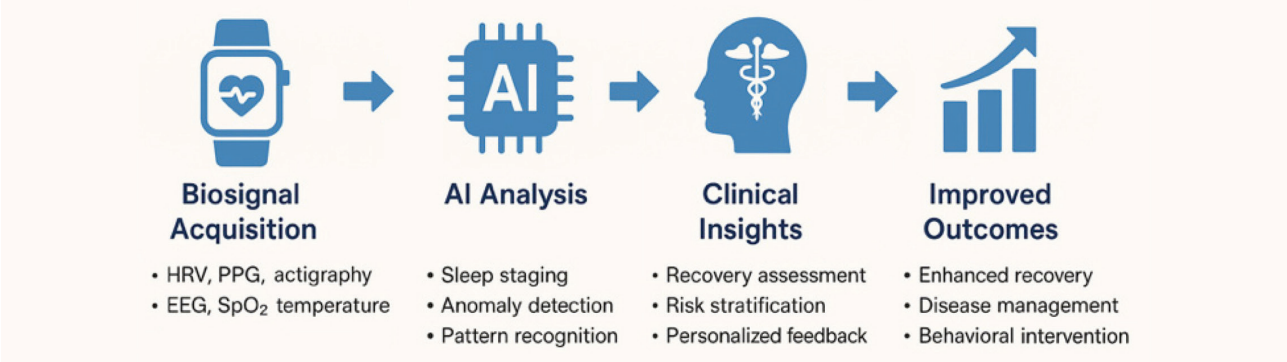


Figure 2. The role of artificial intelligence (AI) in wearable sleep monitoring: From biosignal input to personalized care. HRV: Heart rate variability, PPG: Photoplethysmography, EEG: Electroencephalography.

sleep can support progression to higher workloads with lower risk of overtraining or injury.[8]

6.2. Chronotype, circadian rhythms, and exercise timing

Chronobiological principles are becoming increasingly important in the design of exercise prescriptions, particularly as personalized approaches gain momentum in clinical and athletic settings. Wearable devices capable of monitoring sleep-wake cycles and light exposure – such as the Samsung Galaxy Ring, Muse S, and Withings BeamO– are now used to identify individual chronotypes and detect circadian rhythm disruptions. Recognizing these patterns has several significant implications. For instance, the timing of exercise sessions can be optimized based on chronotype, as individuals with later circadian preferences may respond more favorably to evening training sessions. Additionally, wearables can assist in identifying sleep misalignment in shift workers or individuals experiencing post-viral circadian disturbances, such as those recovering from long COVID. Light exposure monitoring, in turn, can be leveraged as a targeted intervention to support circadian realignment and enhance recovery protocols. Beyond these applications, tracking circadian stability also enables early detection of potential overtraining or underlying illness, especially valuable in populations with chronic fatigue or those undergoing intensive rehabilitation.

6.3. Sleep as a recovery biomarker in rehabilitation

In conditions, such as heart failure, COPD, diabetes, or neurological impairments, sleep data derived from wearables can serve as a low-burden, high-yield biomarker for evaluating recovery status and intervention effectiveness. Changes in sleep efficiency, increased fragmentation, or delayed REM latency may indicate physiological stress or maladaptation even before the onset of subjective symptoms or changes in standard clinical biomarkers.[3,9] Exercise physiologists can utilize these trends to monitor patients' tolerance to progressive training loads, identify stagnation or regression in rehabilitation progress, and coordinate with healthcare providers to optimize medication timing or behavioral strategies, such as managing caffeine or alcohol consumption and minimizing screen exposure before bedtime.

6.4. From data to action: Building a biofeedback loop

The true value of integrating wearables lies in establishing a closed feedback loop between the patient, the exercise specialist, and the data itself. Platforms such as Whoop, Garmin Connect, and Oura Cloud already provide trend dashboards and alert systems that can be connected to telehealth platforms or electronic medical records. Through these systems, patients can receive daily coaching cues tailored to their recovery status, while clinicians are alerted to signs of non-adherence or early physiological warning indicators. Furthermore, these platforms empower patients to actively manage their recovery using self-regulated tools, such as breathwork routines, individualized sleep scheduling, and guided active recovery practices. When sleep metrics are combined with objective exercise testing data –such as the 6-minute walk test (6MWT), VO_2 peak, or strength assessments– the level of care becomes more personalized, ultimately improving safety, adherence, and patient engagement.

7. LIMITATIONS AND FUTURE CHALLENGES

Despite the promise of wearable technologies in advancing sleep monitoring and recovery assessment, several challenges remain before these tools can be fully embedded

into clinical exercise physiology and broader healthcare practice. These limitations span device-level concerns, data interpretation, population equity, and regulatory gaps.

7.1. Accuracy and validation

Most commercially available wearables are not regulated as medical devices and vary widely in their validity and reliability. While many can reasonably estimate total sleep time and sleep onset, accuracy in detecting sleep stages (especially REM and deep sleep) is limited and inconsistent across devices and populations.[2,9] Moreover, there is a lack of standardized validation protocols across manufacturers, which hinders the comparison of data from different devices and weakens clinical decision-making. Although some devices have shown improved agreement with PSG in healthy adults (e.g., Dreem, Oura Ring), data in patients with chronic diseases or sleep disorders remain sparse. While wearable devices offer substantial cost savings over traditional PSG –both in terms of per-unit pricing (200–500 € for wearables versus 800–3,000 € per PSG study) and reduced operational burdens– their economic value must be weighed against diagnostic limitations. Wearables excel in longitudinal monitoring and scalability, enabling proactive management of chronic conditions at a fraction of PSG's cost. However, their inconsistent accuracy in sleep staging and event detection (e.g., apnea episodes) may necessitate confirmatory PSG in diagnostic scenarios, offsetting potential savings. Future cost-benefit analyses should prioritize hybrid models, where wearables screen for abnormalities and triage high-risk patients to PSG, optimizing resource allocation without compromising diagnostic rigor.[2,9]

7.2. Algorithm transparency and proprietary data

Beyond cost and accuracy, the proprietary nature of wearable algorithms creates a "black box" problem. Clinicians and researchers often have no access to raw data or algorithmic logic used to derive sleep metrics, making it difficult to verify or replicate findings. This lack of transparency undermines scientific rigor and limits the interpretability of trends in high-stakes clinical settings.[3,8] While some platforms offer API access or exportable data, this remains the exception rather than the rule. Standardization of outputs and open-source validation initiatives are urgently needed to ensure consistency, credibility, and comparability across devices. Consumer-grade wearable devices and smartphone apps have significantly expanded public access to sleep monitoring tools. However, accuracy remains a major limitation, particularly when compared with the gold-standard PSG. Studies have shown that devices such as the Fitbit and Garmin Vivosmart 4 tend to overestimate total sleep time and underestimate wake periods, especially in individuals with sleep disorders like obstructive sleep apnea.[10] Validation challenges stem from two key issues: (a) Proprietary algorithms that block independent verification, and (b) inconsistent protocols and outcome measures across studies.[18,19] Emerging approaches include benchmarking against PSG, expanding real-world validation trials, and applying multi-sensor fusion techniques that combine PPG (optical blood volume measurement), accelerometry, electrodermal activity (EDA; skin conductance), and ECG to enhance precision.[19] While promising, the performance of these multi-sensor platforms is still influenced by user-specific factors such as body morphology, skin tone, sensor placement, movement artifacts, and environmental noise, all of which can degrade signal quality and alter algorithm outputs.[20] Despite these advancements, disparities in validation methodologies and a persistent lack of regulatory oversight continue to hinder broader clinical adoption.[18,19] To move the field forward, future research must prioritize large-scale validation trials in diverse clinical populations, the development of open-source benchmarking standards, and implementation of federated learning models that enable personalized calibration while protecting user privacy.[13,21,22] These steps are essential for establishing trust, transparency, and clinical relevance in wearable-based sleep monitoring.

8. ARTIFICIAL INTELLIGENCE RISKS AND ETHICAL CONSIDERATIONS

While AI enhances the clinical potential of wearable sleep monitoring, it also raises pressing ethical and practical concerns. A key area of uncertainty lies in the accountability of automated decision-making systems. As wearables become more diagnostic in function –offering personalized recovery scores, adaptive pacing guidance, or alerts for physiological anomalies– the question of liability becomes critical. If an AI-driven platform fails to detect deterioration in sleep or recovery status, or incorrectly advises exercise intensity, responsibility may be unclear: Does it fall on the clinician, the device manufacturer, or the developer of the proprietary algorithm?

Another ethical dimension concerns patient autonomy and informed consent. Most users are unaware of how their data are processed or how algorithmic outputs influence care. The opacity of proprietary algorithms exacerbates this issue, undermining transparency and trust. Clinicians often receive interpreted data without access to the raw signals or algorithm logic, making it difficult to evaluate

the appropriateness of recommendations or to explain them to patients. Moreover, disparities in training data can introduce algorithmic bias, potentially leading to unequal care. If AI models are not validated across diverse populations –including older adults, women, and ethnically diverse groups– automated outputs may systematically misclassify sleep stages or recovery trends, reinforcing health inequities.

To support clearer clinical and regulatory oversight, future research should include direct comparisons between AI-driven and traditional sleep scoring methods. Such comparisons –ideally summarized in standardized tables– would improve the interpretability of wearable outputs and help establish safety margins and intervention thresholds. In parallel, ethical frameworks should be developed to govern the deployment of AI in rehabilitation, emphasizing transparency, accountability, and the right of patients to opt out of algorithmic feedback.

8.1. Health equity and digital access

Populations most likely to benefit from continuous health monitoring –such as older adults, individuals with chronic diseases, and those from lower socioeconomic backgrounds– are paradoxically among the least likely to have access to or feel comfortable using wearable technologies.[17] Multiple barriers contribute to this digital divide, including the high cost of devices and associated subscriptions, limited digital literacy, the absence of age- or disability-friendly interfaces, and the underrepresentation of vulnerable populations in validation studies. Addressing these disparities requires a multi-pronged approach that emphasizes user-centered design, the development of inclusive and representative datasets, and the formation of community partnerships to promote equitable access, engagement, and sustained adoption of wearable solutions in clinical and rehabilitation settings.

8.2. Clinical integration and workflow

For wearable data to meaningfully impact care, it must be seamlessly integrated into clinical workflows. Currently, most data platforms are siloed from electronic health records (EHRs), and clinicians lack the time or training to interpret raw sleep data during routine visits.[10] There is also no consensus on actionable thresholds (e.g., how much HRV decline warrants intervention). Development of clinical decision support tools, automated flagging systems, and interdisciplinary training are essential for implementation in rehabilitation, cardiology, and primary care settings.

8.3. Regulatory and ethical concerns

As wearables become more diagnostic in function, questions of data privacy, liability, and clinical responsibility arise. Who is responsible when a device fails to alert a clinician to deteriorating sleep? What legal protections exist for patients sharing wearable data with insurers or employers?

There is a pressing need for regulatory frameworks that address data ownership, security, and integration standards, while protecting patients from algorithmic bias and misuse of biometric data.

8.4. Gaps in validation and clinical translation

Despite the growing popularity of wearable sleep technologies, critical gaps remain in their validation and translation to clinical use. Most validation studies have been conducted in healthy, middle-aged adults, leaving older adults, individuals with chronic diseases, and those with fragmented or atypical sleep patterns underrepresented. For example, while devices like the Oura Ring and Dreem headband show promising accuracy in general populations, their performance in patients with neurodegenerative disorders or post-stroke remains unclear. Moreover, the absence of standardized validation protocols across manufacturers makes it difficult to compare devices or draw consistent conclusions. Studies often differ in whether they validate total sleep time, sleep staging, or awakening detection, leading to fragmented evidence. A harmonized validation framework based on gold-standard PSG comparisons across diverse populations is urgently needed.

A gap remains between the advanced capabilities of wearables and their use in clinical practice. Despite widespread consumer adoption, wearable data is rarely integrated into electronic health records or used in routine rehabilitation. Many clinicians lack training or confidence in interpreting sleep metrics like HRV or REM percentages. This limits clinical impact, especially when algorithms are proprietary and lack transparency. Bridging this divide will require collaborative validation, open AI outputs, and user-friendly tools that turn raw data into actionable insights.

9. CONCLUSIONS

Wearable sleep monitoring –powered by AI– is transforming how clinicians track recovery, manage chronic conditions, and personalize care. By integrating biosignals like HRV, sleep stages, and circadian rhythms, AI-enabled systems move beyond passive tracking to deliver actionable, individualized feedback in real time.

To fully embed these tools into clinical exercise physiology, critical gaps must be addressed: robust validation across diverse populations, algorithm transparency, and ethical integration into care pathways. AI offers immense potential, but only when its outputs are explainable, interoperable, and aligned with patient-centered outcomes.

Sleep is no longer a passive state; it is a dynamic biomarker of recovery. With validated wearables and intelligent analytics, clinicians can detect maladaptation early, tailor interventions, and empower patients to co-manage their rehabilitation. The future of recovery is personalized, data-driven, and AI-enhanced.

ΠΕΡΙΛΗΨΗ

Φορητοί αισθητήρες και τεχνητή νοημοσύνη για την παρακολούθηση του ύπνου: Εφαρμογές στην αποκατάσταση και στη διαχείριση της υγείας

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Οι φορητοί αισθητήρες επιτρέπουν τη συνεχή και μη επεμβατική παρακολούθηση της υγείας, με εφαρμογές στην κλινική εργοφυσιολογία και αποκατάσταση. Ο ύπνος, ως θεμελιώδης παράγοντας για την ανάρρωση και την προσαρμογή, παραμένει υποτιμημένος στην εξωνοσοκομειακή φροντίδα. Το παρόν άρθρο εξετάζει τις τεχνολογίες φορητής παρακολούθησης του ύπνου –όπως τα έξυπνα ρολόγια, τα δαχτυλίδια, τους υφασμάτινους αισθητήρες και τις κορδέλες κεφαλής– για την ικανότητά τους να καταγράφουν τα στάδια ύπνου, τη μεταβλητότητα του καρδιακού ρυθμού και τα αναπνευστικά πρότυπα. Τα πολυαισθητηριακά συστήματα που ενσωματώνουν φωτοπληθυσμογραφία, επιταχυνσιομετρία και ηλεκτροκαρδιογραφία προσφέρουν βελτιωμένη ακρίβεια στις μετρήσεις. Οι κλινικές εφαρμογές περιλαμβάνουν την παρακολούθηση της ανάρρωσης σε καρδιολογική αποκατάσταση και την έγκαιρη ανίχνευση αναπνευστικών διαταραχών κατά τον ύπνο. Ωστόσο, υπάρχουν και πολλές προκλήσεις, όπως η εγκυρότητα και η αξιοπιστία σε σχέση με την πολυυπνογραφία, περιορισμοί σχετικά με τους αλγόριθμους, ανησυχίες αναφορικά με το απόρρητο δεδομένων και ανισότητες στην ψηφιακή πρόσβαση. Παρά τις δυσκολίες, η φορητή παρακολούθηση του ύπνου εμφανίζει σημαντικές προοπτικές για την εξατομίκευση των συνταγών άσκησης και την παρακολούθηση της αποκατάστασης σε βάθος χρόνου. Μελλοντικές έρευνες θα πρέπει να εστιάσουν στην αυστηρή και διαχρονική επικύρωση των φορητών συστημάτων παρακολούθησης ύπνου σε ετερογενείς πληθυσμούς, στη διαφάνεια, ερμηνευσιμότητα και δυνατότητα ελέγχου των αλγορίθμων, καθώς και στην αξιοποίηση της τεχνητής νοημοσύνης για την παροχή εξατομικευμένης, έγκαιρης και βασισμένης σε αποδείξεις ανατροφοδότησης. Οι εν λόγω προσπάθειες είναι καθοριστικές για τη βελτιστοποίηση της κλινικής εφαρμογής των συσκευών, την υποστήριξη της λήψης αποφάσεων από τους επαγγελματίες υγείας και την ενίσχυση της αποτελεσματικότητας των παρεμβάσεων αποκατάστασης, με τρόπο προσωποκεντρικό και βιώσιμο.

Λέξεις ευρετηρίου: Αισθητήρες, Αποκατάσταση, Τεχνητή νοημοσύνη, Ύπνος

References

1. VITAZKOVA D, KOSNACOVA H, TURONOVA D, FOLTAN E, JAGELKA M, BERKI M ET AL. Transforming sleep monitoring: Review of wearable and remote devices advancing home polysomnography and their role in predicting neurological disorders. *Biosensors (Basel)* 2025, 15:117
2. YOON H, CHOI SH. Technologies for sleep monitoring at home: Wearables and nearables. *Biomed Eng Lett* 2023, 13:313–327
3. KAZANSKIY NL, KHONINA SN, BUTT MA. A review on flexible wearables – recent developments in non-invasive continuous health monitoring. *Sens Actuators A: Phys* 2024, 366:114993
4. LI H, RADIVOJEVIC Z, HEDLUND M, FAHLGREN A, EGGLESTON MS. The patchkeeper: An integrated wearable electronic stethoscope with multiple sensors. *arXiv* 2024, arXiv:2407, 11837
5. LI K, CARDOSO C, MOCTEZUMA-RAMIREZ A, ELGALAD A, PERIN E. Heart rate variability measurement through a smart wearable device: Another breakthrough for personal health monitoring? *Int J Environ Res Public Health* 2023, 20:7146
6. BELABBACI NA, ALAM MAU. HydroTrack: Spectroscopic analysis

prototype enabling real-time hydration monitoring in wearables. *arXiv* 2024, arXiv:2407, 11997
7. BIOXENSOR. BioXensor: Non-invasive continuous glucose monitor. BioXensor Ltd, 2024. Available at: https://www.bioxensor.com/
8. HANDY C, CHAUDHRY MS, QURESHI MRA, LOVE B, SHILLINGFORD J, PLUM-MÖRSCHEL L ET AL. Noninvasive continuous glucose monitoring with a novel wearable dial resonating sensor: A clinical proof-of-concept study. *J Diabetes Sci Technol* 2024, 18:1408–1415
9. ABD-ALRAZAQ A, ASLAM H, ALSAAD R, ALSAHLI M, AHMED A, DAMSEH R ET AL. Detection of sleep apnea using wearable AI: Systematic review and meta-analysis. *J Med Internet Res* 2024, 26:e58187
10. MATHUNJWA BM, KOR RYJ, NGARNKUEKOOL W, HSU YL. A comprehensive review of home sleep monitoring technologies: Smartphone apps, smartwatches, and smart mattresses. *Sensors (Basel)* 2025, 25:1771
11. REZAIE L, NOROUZI E, BRATTY AJ, KHAZAIE H. Better sleep quality and higher physical activity levels predict lower emotion dysregulation among persons with major depression disorder. *BMC Psychol* 2023, 11:171
12. TRAN NT, TRAN HN, MAI AT. A wearable device for at-home obstructive sleep apnea assessment: State-of-the-art and research challenges. *Front Neurol* 2023, 14:1123227
13. LI K, ELGALAD A, CARDOSO C, PERIN EC. Using the Apple Watch to record multiple-lead electrocardiograms in detecting myocardial infarction: Where are we now? *Tex Heart Inst J* 2022, 49:e227845
14. WITHINGS. BeamO: The 4-in-1 health monitoring device. Withings Official Website, 2024. Available at: https://www.withings.com/us/en/beamo
15. WILLIAMS GJ, AL-BARAIKAN A, RADEMAKERS FE, CIRAVEGNA F, VAN DE VOSSE FN, LAWRIE A ET AL. Wearable technology and the cardiovascular system: The future of patient assessment. *Lancet Digit Health* 2023, 5:e467–e476
16. GRAY M, BIRKENFELD JS, BUTTERWORTH I. Noninvasive monitoring to detect dehydration: Are we there yet? *Annu Rev Biomed Eng* 2023, 25:23–49
17. THE LANCET DIGITAL HEALTH. Digital health equity for older populations. *Lancet Digit Health* 2023, 5:e395
18. PHAN D, SIONG LY, PATHIRANA PN, SENEVIRATNE A. Smartwatch performance evaluation for long-term heart rate monitoring. In: *International Symposium on Bioelectronics and Bioinformatics (ISBB)*. Beijing, 2015:144–147
19. SCARDULLA F, COSOLI G, SPINSANTE S, POLI A, IADAROLA G, DO PERNICE R ET AL. Photoplethysmographic sensors, potential and limitations: Is it time for regulation? A comprehensive review. *Measurement* 2023, 218:113150
20. BIRRER V, ELGENDI M, LAMBERCY O, MENON C. Evaluating reliability in wearable devices for sleep staging. *NPJ Digit Med* 2024, 7:74
21. LI X, LI M, TIAN M, LIU Q, ZHOU X, LIU H ET AL. Exploring the potential of a new wearable sleep monitoring device for clinical application. *Biomed Signal Process Control* 2025, 99:106856
22. XIAO Y, WANG H, LIU H. Smart mattresses with embedded multi-sensor systems for AI-assisted sleep tracking. *J Clin Sleep Med* 2024, 20:115–124

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