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Sleep Monitoring Technology: Evolution, Current Landscape, and Future Horizons

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Abstract

Sleep is a fundamental pillar of human health, intricately linked to cognitive function, cardiovascular well-being, and overall quality of life. However, sleep disorders are increasingly prevalent, posing significant public health challenges. Effective management begins with accurate and accessible monitoring. This review comprehensively examines the technological evolution of sleep monitoring, from the clinical gold standard to emerging home-based and wearable solutions. We detail the principles, sensors, and parameters involved, contrasting polysomnography (PSG) with alternatives like actigraphy, ballistocardiography (BCG), and novel sensor-based systems. The discussion extends to multidimensional sleep parameter recognition techniques leveraging artificial intelligence (AI). Furthermore, we analyze the specific context and technological preferences for sleep monitoring in older adults. Finally, we explore future trajectories, including the integration of multi-sensor fusion, advanced materials like graphdiyne for ultra-sensitive sensing, AI-driven edge computing, and innovative intervention methods such as microneedle-based systems. This synthesis aims to provide a holistic view of the field, highlighting technological convergence as the key to personalized, precise, and preventive sleep healthcare.

Keywords

Sleep Monitoring, Polysomnography, Wearable Sensors, Actigraphy, Ballistocardiography, Artificial Intelligence, Elderly Care, Sensor Fusion.

1. Introduction

Sleep occupies approximately one-third of the human lifespan, serving critical restorative functions for the brain and body. High-quality sleep is essential for memory consolidation, metabolic regulation, immune function, and emotional stability [1,2]. Conversely, sleep disturbances and disorders such as insomnia, sleep apnea syndrome (SAS), circadian rhythm disorders, and restless legs syndrome, are widespread, with reported prevalence rates ranging from 10% to over 30% in various populations [3,4]. In China alone, over 400 million individuals are affected by sleep problems [5]. The consequences are severe, elevating the risks for cardiovascular diseases, diabetes, obesity, depression, anxiety, and cognitive decline [6]. Among the most significant is Obstructive Sleep Apnea (OSA), a condition characterized by repeated airway collapse during sleep, which, if untreated, can more than triple the risk of stroke and cardiovascular mortality [7,8].

Given this profound impact on health and societal productivity, accurate sleep assessment is paramount. It serves a dual purpose: the diagnosis of sleep disorders and the evaluation of sleep-aid intervention efficacy, forming a dynamic feedback loop for treatment optimization [9]. Traditionally, sleep medicine has relied on subjective reports, which are susceptible to bias and inaccuracy, particularly in older adults or those with cognitive impairment who may under-

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report problems [10,11]. This underscores the necessity for objective measurement tools. The pursuit of such tools has evolved from cumbersome, laboratory-bound equipment to a burgeoning field of accessible, user-friendly technologies suitable for long-term, home-based monitoring. This review traces this technological evolution, examines the current ecosystem of sensors and analytical methods, and envisions the future of sleep monitoring as a cornerstone of personalized digital health.

2. The Evolution of Sleep Monitoring Technologies

2.1. The Gold Standard: Polysomnography (PSG) and Its Limitations

The undisputed gold standard for diagnosing sleep disorders is in-laboratory Polysomnography (PSG). PSG is a multi-parametric test that simultaneously records a suite of physiological signals during sleep [12,13]. Core measurements include electroencephalography (EEG) for brain wave activity to stage sleep (wake, NREM stages 1-3, REM sleep), electrooculography (EOG) for eye movements, electromyography (EMG) for muscle tone (typically submental and limb), electrocardiography (ECG) for heart rate and rhythm, respiratory effort (via belts), airflow (via thermistor or nasal pressure cannula), and blood oxygen saturation (via pulse oximetry) [14,15]. This comprehensive data allows clinicians to identify apneas, hypopneas, limb movements, and atypical brain activity.

Despite its diagnostic authority, PSG suffers from significant drawbacks that limit its scalability and utility for longitudinal monitoring [9,16]. First, it is highly intrusive. Patients must sleep in an unfamiliar laboratory environment while connected via over 50 electrodes and sensors, a setup that invariably alters the very behavior—natural sleep—it aims to measure. Discomfort and the "first-night effect" can skew results [17]. Second, it is resource-intensive. The equipment, such as advanced systems like the German Sonmo™, is extremely costly, requiring substantial capital investment [9]. The need for specialized technicians for setup and expert clinicians for interpretation further escalates expenses and creates access bottlenecks, leading to long waiting times [18]. Third, it provides only a single-night snapshot. Sleep exhibits considerable night-to-night variability [19,20]. A one-night PSG may miss intermittent disorders or fail to capture the typical sleep pattern of an individual, potentially leading to misdiagnosis or underestimation of severity [21]. These limitations of high cost, low comfort, poor accessibility, and lack of longitudinal data have driven the search for alternative monitoring paradigms.

2.2. The Shift to Ambulatory and Home-Based Monitoring

The recognition of PSG's limitations catalyzed the development of ambulatory and home-based monitoring solutions. The initial drive was to maintain diagnostic capability outside the lab. Home Sleep Apnea Testing (HSAT) devices, which typically focus on cardiorespiratory parameters (airflow, effort, oximetry, heart rate), emerged as a cost-effective alternative for diagnosing moderate-to-severe OSA in uncomplicated patients [22]. While simpler than PSG, many HSAT devices still require technical setup and lack full sleep staging.

Parallel to simplified clinical devices, the field witnessed the rise of consumer-oriented objective monitoring focused on longitudinal tracking rather than one-off diagnosis. This shift was fueled by advances in microelectronics, sensor miniaturization, and wireless connectivity. The goal evolved from detailed clinical diagnosis to convenient, long-term sleep quality assessment, trend identification, and intervention feedback in a person's natural sleeping environment. Studies have shown that sleep at home can differ from sleep in the lab, often with improved sleep efficiency and architecture in the home setting, validating the pursuit of home-based technologies [23]. As shown in Figure 1, this illustrates a comparison of different sleep monitoring technologies.

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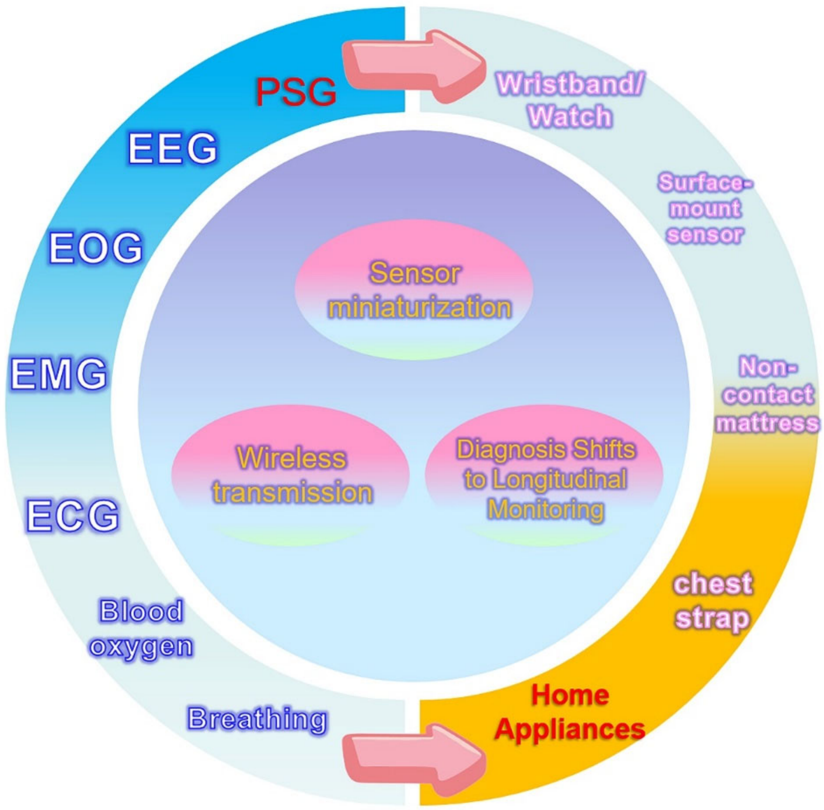

Figure 1. Comparison of Sleep Monitoring Technology Paradigms

3. The Current Landscape of Sleep Monitoring Technologies and Methods

Contemporary sleep monitoring methods can be broadly classified into contact-based (wearable and non-wearable) and non-contact-based systems, each with distinct sensor types, measured parameters, and trade-offs between accuracy, comfort, and cost. Figure 2 clearly illustrates the comprehensive classification of current sleep monitoring technologies.

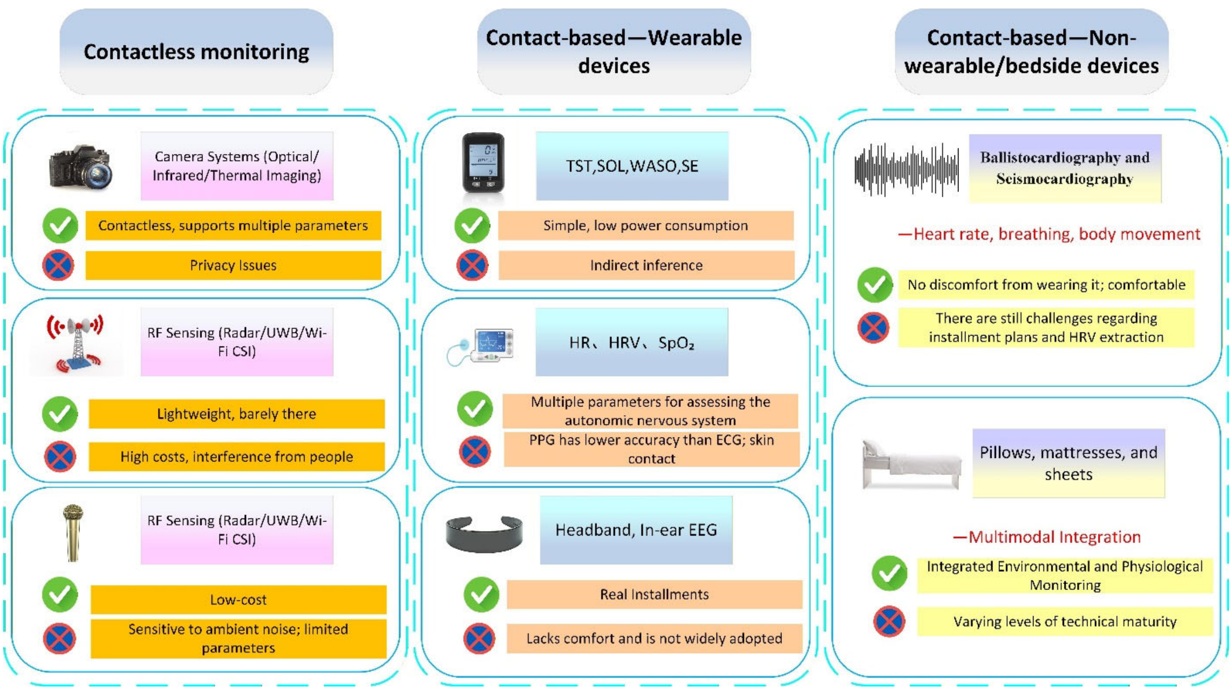

Figure 2. Comprehensive Classification of Current Sleep Monitoring Technologies

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3.1. Non-Contact Monitoring Methods

Non-contact methods aim to provide completely unobtrusive monitoring, ideal for long-term use without burdening the user.

(1) Camera-Based Systems: Optical, infrared (IR), and depth cameras can monitor respiration rate and body posture by analyzing chest/abdominal movement or body contour [24,25]. Thermal cameras can detect breathing through temperature fluctuations near the nostrils [26]. While promising for posture and breathing analysis, they cannot directly measure vital signs like heart rate or brain activity for sleep staging. A major, often prohibitive, concern is privacy, as continuous video recording in the bedroom is typically unacceptable [27].

(2) Radio Frequency (RF) Sensing: This category includes technologies like Doppler radar, Frequency-Modulated Continuous Wave (FMCW) radar, Impulse Radio Ultra-Wideband (IR-UWB) radar, and millimeter-wave radar. These systems emit low-power RF signals and analyze the reflected waves, which are modulated by micro-movements of the chest wall (respiration) and the body (ballistocardiographic signals from the heartbeat) [28,29]. They can extract heart rate, heart rate variability (HRV), and respiratory rate without physical contact [30,31]. Some advanced systems claim to detect sleep apnea [32]. However, they are generally expensive, and their accuracy can degrade in multi-person environments or with significant body movement [33]. Commercial Wi-Fi routers have also been repurposed to sense respiration and gross body movement by analyzing channel state information perturbations, though they lack the precision for detailed vital sign extraction [34,35].

(3) Acoustic Monitoring: Microphones, often embedded in smartphones or specialized devices, are primarily used for snoring event detection [36,37]. While low-cost and simple, audio-only analysis is easily confounded by environmental noise and cannot assess other critical sleep parameters like sleep stages or oxygen levels.

3.2. Contact-Based Monitoring: Wearable Devices

Wearables represent the most prevalent form of consumer sleep tracking, balancing usability with a growing set of capabilities.

(1) Actigraphy: The cornerstone of wearable sleep assessment for decades, actigraphy uses a MEMS (Micro-Electro-Mechanical Systems) accelerometer, typically worn on the wrist, to measure movement. Periods of immobility are inferred as sleep, and movement as wakefulness. Algorithms generate metrics like Total Sleep Time (TST), Sleep Onset Latency (SOL), Wake After Sleep Onset (WASO), and Sleep Efficiency (SE) [38,39]. A large-scale scoping review on home-based monitoring in older adults found actigraphy to be the overwhelmingly dominant technology, used in 43 of 48 wearable studies, with TST, WASO, and SE being the most reported parameters [40]. Its strengths are its simplicity, low cost, long battery life, and high user compliance. Its critical weakness is its indirect nature; it infers sleep from the absence of movement, which can lead to misclassification (e.g., lying still while awake is scored as sleep) [41]. Its accuracy for sleep staging (differentiating light, deep, and REM sleep) is poor compared to PSG.

(2) Advanced Physiological Wearables: To overcome actigraphy's limitations, newer wearables incorporate additional sensors:

Photoplethysmography (PPG): Common in smartwatches and rings, PPG uses green LED light to detect blood volume changes in capillaries, providing continuous heart rate and pulse rate variability (a proxy for HRV) [42]. HRV, a marker of autonomic nervous system activity, is valuable for stress assessment and shows promise in sleep quality evaluation and stage differentiation [43,44].

Electrocardiography (ECG): Some chest straps or smartwatches offer single-lead ECG, providing more accurate R-R intervals for HRV analysis than PPG [45].

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Body Temperature: Wrist or core temperature sensors can track circadian rhythm and detect nighttime awakenings [46].

Pulse Oximetry: Wearable finger clips or ring sensors measure blood oxygen saturation (SpO_2), crucial for detecting hypopneas and apneas associated with OSA [47].

Electroencephalography (EEG): A new generation of wearable headbands or ear-EEG devices aims to bring brainwave monitoring out of the lab. These devices use dry electrodes to record limited-channel EEG, enabling true sleep stage classification (NREM, REM) at home [48,49]. While more accurate for staging than actigraphy, they are less comfortable for all-night wear and not yet mainstream.

3.3. Contact-Based Monitoring: Non-Wearable (Bed-Based) Devices

These systems integrate sensors into the sleep environment, offering a compromise between the obtrusiveness of wearables and the limitations of non-contact methods.

(1) Ballistocardiography (BCG) and Seismocardiography (SCG): BCG measures the minute recoil forces of the body caused by cardiac ejection of blood, while SCG measures local chest wall vibrations. For sleep, BCG is typically implemented using sensor mats placed under the mattress or bedsheet [50]. These mats employ various sensor types:

Pressure Sensor Arrays: Sheets or mats with grids of pressure sensors can detect breathing patterns, body movement, and gross posture [51,52].

Piezoelectric Films: Materials like Polyvinylidene Fluoride (PVDF) or Electromechanical Film (EMF) generate electrical charge in response to mechanical stress, sensitive enough to detect heartbeat and respiration vibrations [53,54].

Strain Sensors: Fiber-optic or other strain sensors can be woven into fabrics to detect similar forces [55,56].

MEMS IMUs: Accelerometers and gyroscopes embedded in mats can capture BCG/SCG signals [57,58].

BCG systems are promising as they require no conscious wear effort, are relatively comfortable, and can capture heart rate, respiratory rate, and movement. However, accurately deriving HRV and detailed sleep stages from BCG alone remains challenging [59]. Their adoption in research, particularly for older adults, is noted but less common than actigraphy [40].

(2) Smart Bedding: Pillows, mattresses, and sheets are increasingly being equipped with sensor suites (e.g., combination of pressure, temperature, and sound sensors) to provide a holistic view of the sleep environment and occupant [60,61].

3.4. Novel Sensing Materials and Paradigms

Research continues to push the boundaries of sensor sensitivity and form factor. A notable example is the development of flexible respiratory sensors using novel carbon nanomaterials. Xu et al. demonstrated a humidity sensor based on amino-modified graphdiyne (NH_2-GDY) [62]. Graphdiyne's unique nanoporous structure and the hydrophilic amino groups enable ultra-fast adsorption/desorption of water molecules from exhaled breath. This sensor achieved remarkable response and recovery times (0.2 s and 1.6 s) and high sensitivity, allowing it to distinguish between normal, deep, and apneic breathing patterns when integrated into a wearable mask or system [62]. Such material advances point toward future sensors that are not only flexible and wearable but also possess laboratory-grade sensitivity for specific physiological parameters like respiration quality.

4. Sleep Parameter Recognition and the Role of Artificial Intelligence

Raw sensor data is meaningless without robust algorithms to translate signals into actionable sleep parameters. The process typically involves two stages: **feature extraction** and **pattern**

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recognition/classification. As shown in Figure 3, it clearly illustrates the artificial intelligence-driven sleep parameter identification process and technological evolution, which perfectly corresponds to the content described in the following sections.

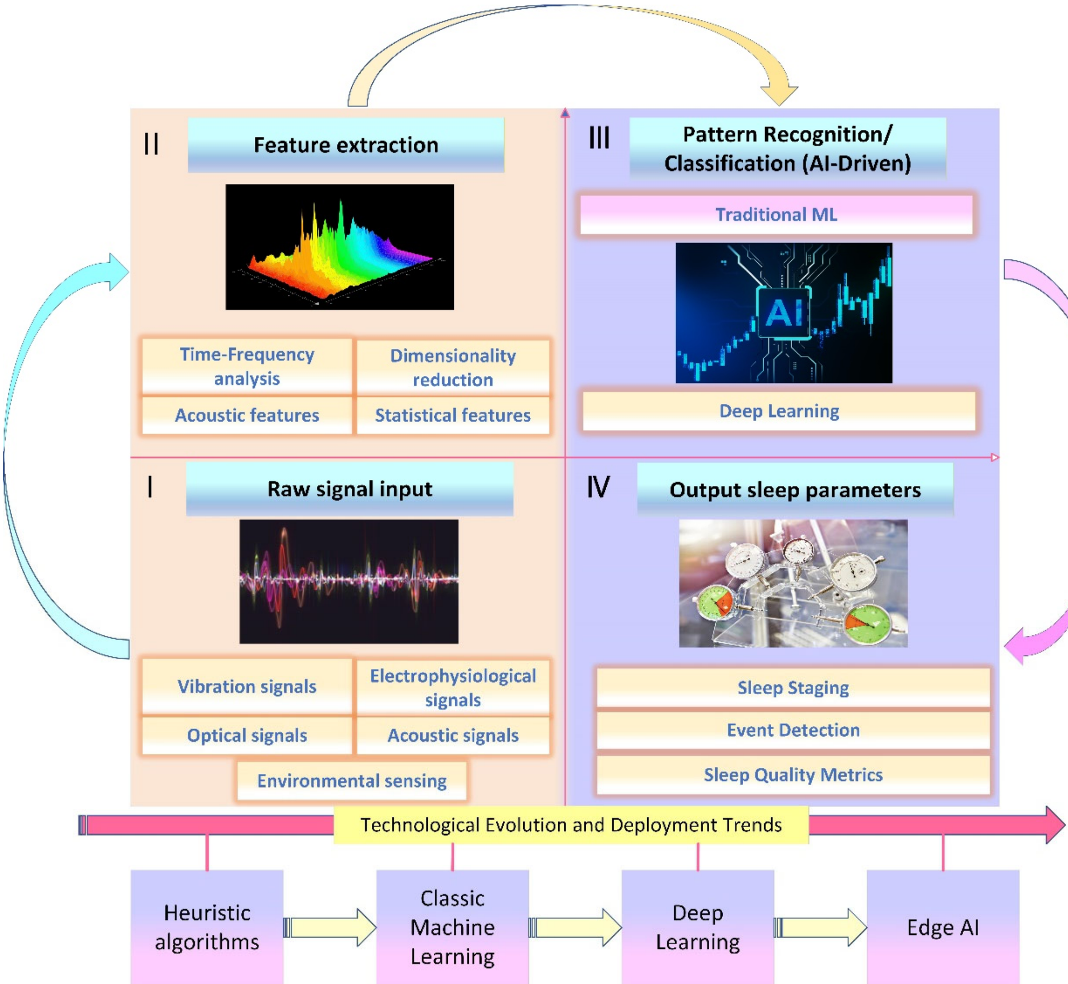

Figure 3. AI-Driven Sleep Parameter Recognition Process and Technological Evolution

4.1. Feature Extraction

This step transforms raw time-series data (vibration, optical, electrical) into a set of meaningful descriptors. For vibration signals (accelerometer, BCG), common methods include time-frequency analysis (wavelets), statistical features (mean, variance, kurtosis), and dimensionality reduction techniques like Principal Component Analysis (PCA). For acoustic signals (snoring), features like Zero-Crossing Rate, Mel-Frequency Cepstral Coefficients (MFCC), spectral entropy, and energy are commonly used [63,64]. The choice of features significantly impacts downstream classification performance.

4.2. Pattern Recognition and AI-Driven Classification

This is where machine learning (ML) and deep learning (DL) have revolutionized sleep monitoring.

(1) Sleep-Wake and Sleep Stage Classification: While heuristic algorithms (like the Cole-Kripke algorithm for actigraphy) are still used, ML models offer superior accuracy. Models such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (KNN) have been applied to features from actigraphy, HRV, and respiration to classify sleep vs. wake or even rudimentary sleep stages [65,66]. Deep Learning, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) like Long Short-Term Memory (LSTM) networks, has set new benchmarks. These models can take raw or minimally processed signal

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windows (e.g., from EEG, PPG, or accelerometry) and automatically learn hierarchical features to perform complex tasks like multi-class sleep stage (N1, N2, N3, REM, Wake) scoring [67,68]. Recent architectures like Transformers and State Space Models (e.g., Mamba) are beginning to be explored for their potential in modeling long-range dependencies in sleep data [69,70].

(2) Event Detection: AI is crucial for identifying specific pathological events. For snoring detection, CNNs and hybrid CNN-LSTM models are trained on audio spectrograms to distinguish snores from other nighttime sounds with high accuracy (>95%) [71,72]. Similarly, apnea/hypopnea events can be detected from patterns in respiratory effort, airflow (from thermistor or ambient temperature/humidity sensors like the NH_2-GDY sensor), heart rate, and SpO_2 signals using a variety of classifiers [73,74].

(3) The Challenge of Edge Computing: Many state-of-the-art DL models are computationally heavy, requiring cloud processing, which raises concerns about data privacy, latency, and connectivity [75]. The future trend is toward **lightweight models** deployable on edge devices (microcontrollers within wearables). Research into model compression, knowledge distillation, and efficient neural architecture design (e.g., depthwise separable convolutions) is critical for making advanced AI a reality in low-power, real-time sleep monitors [76,77].

5. Special Considerations: Sleep Monitoring in Older Adults

The aging population has distinct sleep patterns and monitoring needs. Older adults commonly experience advanced sleep phase, reduced slow-wave sleep, increased sleep fragmentation (higher WASO), and more frequent naps [78]. Furthermore, they are at higher risk for sleep disorders like OSA and insomnia, and may have co-morbidities that affect sleep.

The scoping review by Ghazi et al. provides a focused snapshot of home-based objective monitoring in this demographic [40]. Its key findings align with and illuminate broader trends:

(1) Technology Dominance: Actigraphy wristwatches are the near-universal tool in research, prized for their balance of acceptability, cost, and ability to measure key macro-parameters (TST, WASO, SE) over multiple nights.

(2) Parameter Focus: Studies overwhelmingly report on macro-architectural parameters (TST, WASO, SE) rather than micro-architecture (sleep stages). This reflects both the limitations of the dominant technology (actigraphy) and a research focus on sleep quality and continuity, which are strong predictors of health outcomes in aging.

(3) Limited Sleep Stage Monitoring: Only 6 of the 54 reviewed studies assessed sleep stages, using EEG headbands, BCG, or radiofrequency sensors [40]. This highlights a significant gap and opportunity. As comfortable, accurate EEG wearables (headbands, ear-EEG) mature, they could revolutionize the understanding of sleep architecture and its link to neurodegenerative diseases (e.g., the association between NREM disruption and Alzheimer's pathology) in older adults at home [79,80].

(4) Multidimensional Associations: The review powerfully illustrates that sleep parameters in older adults are not isolated metrics. They are associated with a wide array of predictors and outcomes: **Health-related** (frailty, grip strength, cognitive decline), **Environmental** (exterior housing noise, light exposure, temperature), **Behavioral** (in-bed screen use), **Social** (relationship status), and **Interventional** (response to exercise) [40]. This underscores that effective sleep monitoring for healthy aging must be interpreted within a broad biopsychosocial context.

To summarize the above elaborations, as shown in Figure 4, it clearly presents various scenarios and correlations of home-based sleep monitoring for older adults.

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Figure 4. Current status, gaps and multidimensional associations of home-based sleep monitoring for older adults

6. Future Perspectives and Concluding Remarks

The trajectory of sleep monitoring technology is clear: moving from infrequent, clinical snapshots to continuous, integrated, and intelligent ecosystem of health management. Several convergent trends will shape the future.

(1) Multi-Sensor Fusion and Heterogeneous Data Integration: No single sensor is perfect. The future lies in **sensor fusion**, combining complementary data streams (e.g., wrist PPG/acceleration + bed BCG + ambient sound/temperature) to overcome individual limitations and achieve PSG-approaching accuracy in a home setting [81,82]. For instance, actigraphy's movement data can be refined by heart rate data from PPG; BCG's cardiac metrics can be validated by wearable ECG. Fusion algorithms, often based on DL, will synthesize these signals for robust sleep staging, apnea detection, and sleep quality scoring.

(2) Material Science and Novel Sensor Designs: Advances in flexible and stretchable electronics, biodegradable materials, and novel active materials like **graphdiyne** will lead to the next generation of sensors [62]. These sensors will be more sensitive, more comfortable (skin-like or textile-integrated), and capable of detecting new biomarkers (e.g., cortisol in sweat, specific volatile organic compounds in breath) that provide deeper physiological insight.

(3) Advanced AI and Personalization: AI will evolve from a classification tool to a predictive and personalized analytic engine. Algorithms will learn individual baselines, detect subtle deviations that signal emerging health issues, and provide personalized sleep hygiene recommendations. Federated learning could enable model improvement across populations while preserving data privacy [83]. Furthermore, the integration of sleep monitoring data with

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other health data (activity, nutrition, medication) via digital platforms will offer a truly holistic view of an individual's well-being.

(4) Closed-Loop Intervention Systems: Monitoring will increasingly be linked to intervention. The concept of **microneedle-based sleep aid systems** exemplifies this frontier [84]. These systems could combine soluble microneedles for transdermal delivery of herbal sleep aids and metal microneedle arrays for transcutaneous electrical stimulation at acupoints. A closed-loop system would use real-time sleep stage or quality data from a wearable (e.g., EEG headband) to trigger or modulate the intervention (e.g., initiate electrical stimulation upon detecting prolonged wakefulness), creating a dynamic, responsive therapy [85,86]. This represents the ultimate convergence of monitoring and treatment.

(5) Focus on User-Centric Design and Equity: For technology to be effective, it must be adopted. Future devices must prioritize **user experience**: comfort, ease of use, long battery life, and intuitive data presentation. This is especially critical for older adults. Furthermore, efforts must be made to ensure these technologies are accessible and validated across diverse populations to avoid exacerbating health disparities.

In conclusion, the field of sleep monitoring has undergone a profound transformation, driven by the dual engines of technological miniaturization and computational intelligence. From the cumbersome wires of the sleep lab, we have moved to wrist-worn devices and sensor-embedded bedrooms. The current landscape is diverse, offering a spectrum of solutions balancing accuracy, comfort, and cost. The future points toward invisible, multi-modal sensing systems powered by AI, capable of not only diagnosing disorders but also predicting risks, personalizing interventions, and integrating seamlessly into a proactive healthcare paradigm. As these technologies mature and converge, they hold the promise of revolutionizing our approach to sleep, transforming it from a passive biological process into an actively managed pillar of lifelong health and well-being.

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