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Review Article

Others Section

Use of Artificial Intelligence in Analysing Recent Trents in Sleep Disorder: A Comprehensive Review

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ABSTRACT

Sleep disorders affect a large proportion of the population and are traditionally diagnosed using nocturnal polysomnography; however, they are laborious and expensive. Emerging Artificial Intelligence (AI) has modified the diagnosis and disease management strategies for sleep disorders. Moreover, machine learning and deep learning algorithms may precisely recognise disorders including narcolepsy, insomnia, and Obstructive Sleep Apnoea (OSA) utilising intricate electrophysiological information. These modalities aid in evaluating sleep patterns, thereby facilitating earlier diagnosis and tailored management. Integration of the Internet of Medical Things (IoMT) with peripheral devices enables real-time monitoring of past clinical settings. AI-driven tools optimise clinical workflows, minimise healthcare costs, and reduce dependency on manual assessment. Moreover, AI improves clinical outcomes and treatment adherence by enabling accurate phenotyping and personalised treatment modifications. Despite requiring specific procedures, unpredictable sensor information, data privacy issues, algorithm robustness and regulatory compliance are under investigation. The current comprehensive review emphasises the transformative role of AI in sleep medicine, highlighting its capacity to enhance patient quality of life, optimise management strategies and improve diagnostic accuracy.

Keywords: Machine Learning, Obstructive sleep apnoea, Polysomnography

INTRODUCTION

Proper sleep is essential for routine cognitive functioning and emotional and physical well-being, while inadequate sleep is associated with several negative health consequences. Millions of individuals are impacted by sleep disorders, worldwide, including Rapid Eye Movement (REM), sleep behaviour disorders, insomnia, and OSA [1]. OSA affects around one billion individuals, with approximately 425 million individuals being diagnosed with moderate-to-severe cases and approximately 82% remaining undiagnosed [2]. While REM sleep behaviour disorder estimated prevalence of 0.5-1% among adults, elevating to nearly 5-13% among elders [3]. Insomnia represents major sleep disorders worldwide, with 30-35% of individuals experiencing insomnia symptoms, while 10-15% experience chronic insomnia, significantly impairing quality of life [4]. Nearly half of Americans report daytime drowsiness, and 35-50% experience insomnia symptoms annually, according to the National Sleep Foundation [4]. In India, recent research indicates that 10% to 30% of the urban population is affected by sleep disorders, with insomnia being more prevalent in elderly adults and women by up to 50% to 60% [5].

Traditionally, sleep assessment was based on Polysomnography (PSG), wherein patients underwent overnight intensive care with a variety of sensors—such as Electroencephalography (EEG), Electro-oculography (EOG), and Electromyography (EMG) for capturing physiological signals [6]. This data is analysed in accordance with American Academy of Sleep Medicine (AASM) guidelines for delineating sleep phases and determining dysfunctions that probably indicate disorders [6]. Nonetheless, traditional methods are costly, and intrusive, resulting in variable and delayed outcomes. Furthermore, Continuous Positive Airway Pressure (CPAP) treatment is hampered by adherence challenges, exacerbating public health impact [7]. However, promising solutions for overcoming limitations of conventional treatment in diagnosing and managing sleep disorders are delivered by progression in AI techniques. Early AI models have efficiently removed critical insights from complicated PSG data, recognising sleep anomalies with precision comparable with skilled clinicians. Notably, AI-powered algorithms that utilise single-lead Electrocardiogram (ECG) signals offer a cost-effective and less intrusive alternative to full PSG, thereby facilitating the identification of conditions such as insomnia and OSA [8].

Furthermore, the integration of AI with digital health technologies, particularly the IoMT, represents a revolutionary change in the field of sleep medicine [9]. IoMT facilitates continuous, remote monitoring through interconnected peripheral sensors, which, when combined with AI, offer real-time sleep analysis and personalised treatment recommendations [8,9]. Such innovations significantly enhance diagnostic efficiency and optimise patient care by offering tailored, and data-driven interventions that discourse specific patient requirements while minimising the need of conventional diagnostic interventions. Hence, the present comprehensive review aimed to evaluate the role of AI in the diagnosis, monitoring and management of sleep disorders, along with its potential to resolve conventional practices and resolve clinical practices.

Search Strategy: A literature search was conducted using PubMed, Scopus, Web of Science, Google Scholar, and ScienceDirect for articles published between January 2000 and March 2026. Keywords and MeSH terms including "Artificial Intelligence", "Machine Learning", "Deep Learning", "Sleep Disorders", "Obstructive Sleep Apnoea", "Insomnia", "Polysomnography", and "Internet of Medical Things" were used.

Original articles, systematic reviews, meta-analyses, clinical studies, and guidelines published in English language were included. Duplicate studies, conference abstracts without full text, and non English articles were excluded. Relevant articles were screened based on title, abstract, and full-text relevance to AI applications in sleep disorder diagnosis and management.

Understanding Sleep Disorders

Epidemiology and burden of sleep disorders: Sleep disorders pose significant public health concerns, affecting population globally. It is estimated that between 50 and 70 million Americans suffer from chronic sleep and wakefulness disorders [10]. Epidemiological data reveal that the prevalence of sleep problems varies markedly by region; for example, America reports a prevalence of 64.13%

compared to 20.23% in Europe and 21.31% in the Western Pacific [11]. Among older adults in America, the prevalence of poor sleep quality reaches 47.12% and sleep problems 26.97%, with worsened sleep problems rising sharply from 15.14% in 2020 to 47.42% in 2021 [11]. This suggests influence of geographical variation on sleep disturbances due to varied socioeconomic status, healthcare accessibility, ethnic disparity, and public health responses across regions. Furthermore, Du M et al., highlighted marked regional variations, with pandemic-associated stressors and varying containment measures elevating sleep issues in specific regions, particularly during Coronavirus Disease 2019 (COVID-19) periods [11]. Furthermore, over 40% of respondents report experiencing fair to poor sleep quality, approximately 13% struggle with frequent insomnia, and 9% consistently experience daytime fatigue in conjunction with symptoms, indicative of OSA [12].

For a variety of sleep disorders, more comprehensive prevalence rates have been documented: 24-50% for OSA, 32.1% for General Sleep Disturbance (GSD), 43.2% for insufficient sleep, 8.2% for insomnia, 5.3% for circadian rhythm sleep disorder, 6.1% for parasomnia, and 5.9% for hypersomnolence [13].

The epidemiology of India is consistent with global trends but presents additional obstacles due to socio-economic and demographic fluctuations. Urban populations report a prevalence of 36% for sleep disturbances, with insomnia and poor sleep quality as 67% more prevalent among women than men [14]. Kaur T et al., discovered that 11.27% of individuals experience poor sleep quality and 40.81% manifest short sleep duration, [15] while two meta-analyses reported pooled prevalences of 40% and 36.73% among the general population [16,17]. Significant regional disparities in India are exacerbated by the high underdiagnosis rates, limited availability of specialised sleep centers, and cultural and lifestyle variations [15].

AI In Sleep Medicine

What is AI?

Artificial Intelligence (AI) is the development of computer algorithms and software systems that learn and improve with experience. It focuses on developing models that can interpret complex data and make judgments or predictions. Machine learning (ML), a fundamental field of AI, analyses massive, real-world datasets using mathematical, statistical, and probabilistic methodologies [18]. For improving task-related performance, ML models are trained iteratively with parameters attuned accordingly. ML approaches are categorised into supervised and unsupervised learning with models trained to classify, recognise, or conduct regression tasks utilising labeled datasets including PSG waveforms and known results in supervised learning. Unsupervised learning, on the other hand, uses unlabeled data to detect hidden patterns or cluster data points in the absence of predetermined targets [19]. Model training entails adjusting features, hyperparameters, and configurations through trial and error to ensure strong input-target correlations and low redundancy [19]. The overarching goal of AI is to develop artificial general intelligence, or systems capable of versatile, human-like learning and problem solving [18].

Role of AI tools utilised in Sleep Research: AI techniques have altered sleep research by improving data collection, analysis, and interpretation. AI-powered solutions systematise PSG dispensation, including sleep stage scoring and respiratory event recognition, minimising manual labor and inter-scorer distinction [18]. Advanced ML and Deep Learning (DL) techniques extract significant biomarkers from multimodal inputs including EEG, EOG, and EMG, elevating diagnostic precision for sleep disorders including OSA, insomnia, and parasomnias [1].

Beyond signal processing, AI delivers diagnostic assistance and prognostic modeling by determining complicated outlines in large-scale data. Such outcomes assist in foreseeing sleep disorder advancement and controlling tailored therapy [8]. The integration of AI with electronic health records and wearable data enables remote, continuous sleep monitoring. Wearable DL models have demonstrated increased diagnostic accuracy, attaining nearly 86% in detecting sleep problems, and around 95-99% precision in controlled ECG-based models [20]. For quality evaluation and sleep staging, DL-enabled wearables report around 76% agreement with PSG and area under curve around 0.94, assisting their role in bridging the gap between lab-based and home-based monitoring [21].

AI also advances sleep neurobiology. ML classifiers analysing EEG data can aid in diagnosing sleep-wake challenges and forecast the preliminary neurodegenerative disorders [1]. Iterative assistance enhances prediction performance in Artificial Neural Networks (ANN), implemented utilising DL architecture [9]. Alom MS et al., investigated ANN models for sleep disorder diagnosis and exposed that bagging and boosting coordinates higher precision of around 94.7%, followed at 92.9% with weighted average method [22].

Barriers and Challenges of AI Integration in Sleep Healthcare

AI incorporation into sleep medicine has great potential to enhance the consistency of diagnosis and efficiency of clinical practice but harbors few challenges that need to be addressed to ensure confidence in the safe and effective use of AI. One crucial problem is training and validating AI systems. As these models are trained on the limited data, they risk inadvertently capturing and propagating the biases of the training data, potentially impinging upon both fairness and clinical utility despite best efforts to design appropriately [18].

AI models trained on source data from controlled laboratory settings are likely to suffer from poor generalisability when deployed to real world clinical scenarios because of domain shifts in data distributions. This is a challenging problem affecting prediction accuracy and calls for robust domain adaptation methods that can preserve model consistency across different clinical domains [18,22].

Interoperability with established Electronic Medical Records (EMRs) and clinical workflows add complexity to patient data safety, particularly in cloud-based solutions. Ensuring data privacy is still challenging during the process of AI model inference. Moreover, “black box” nature of AI models (i.e., complicated algorithms like deep neural networks whose internal decision-making strategies are difficult to be interpreted by humans) can impede clinician faith, highlighting the importance of explainable AI to promote adoption [23]. Regulatory obstacles also remain. Regulatory interventions involve post-marketing surveillance and follow-up for ensuring data safety, but can reduce innovation. Good ML practices including accurate data distinction and hyperparameter tuning are essential to minimise overfitting, while data privacy should be ensured through appropriate governance measures. Model performance varies with geographical patterns, with differences in environmental, ethnicity, and medical access impacts disease patterns and physiological signals. [24]. Furthermore, behavioural variations, including sleeping habits, wearable device adherence and stress levels along with occupational factors such as shift work can alter circadian rhythms and cardiometabolic parameters, influencing data outcomes and quality. In addition, age-associated physiological parameters and pandemic/epidemic conditions can necessitate diversified training datasets and modify population healthcare utilisation [18].

AI-based Diagnosis of Sleep Disorders

Role in sleep staging and PSG: AI tools have significantly enhanced sleep staging and PSG through automated scoring and identifying complicated sleep microstructures, thereby reducing burden on sleep technologists. Sleep is categorised into wakefulness, Non Rapid eye Movement (NREM) sleep stages N1, N2, and N3, and

REM sleep [23]. While PSG offers macro size illustration of sleep architecture, it often skips micro-elements including microarousal and Cyclic Alternating Patterns (CAPs). These features are critical biomarkers of sleep instability and are associated with disorders like OSA and insomnia; notably, their occurrence can diminish with CPAP treatment [1].

Automated recognition of OSA: AI tools have enabled automated OSA detection, providing a viable alternative to conventional diagnostic techniques. OSA is characterised by recurrent episodes of partial (hypopnoea) or complete (apnoea) upper airway obstruction lasting ≥10 seconds during sleep, causing cortical arousals or reduced oxygen saturation levels. The Apnoea Hypopnoea Index (AHI) is usually used to determine OSA severity, categorised as mild (5≤AHI<15), moderate (15≤AHI<30), and severe (AHI≥30) [25].

The Home Sleep Apnoea Testing (HSAT) has emerged as a cost-efficient and manageable decision. The AASM recommends HSAT with technically sound devices for individuals who are at moderate to severe risk [18]. Recent developments have made it possible to utilise AI-driven wireless wearable devices like smartwatches, rings, and sensors worn on chest- or belly to pre-diagnose and diagnose OSA [20]. These devices can directly record respiratory signals and body positions, and represent performance with reported accuracies ranging between 70% to 100%, sensitivities between 76% to 100%, and specificities between 29% and 99% [20].

New sensor technologies such as capacitive sensors and accelerometers are working better for calculating respiration since they are easy to use and cheap. Soomirang wireless abdomen-worn sensor, which uses an MLP-Mixer DL model, is a good example. The correlations for sleep time and AHI are 0.9 and 0.95, respectively, with accuracy, sensitivity, and specificity values as 97.14%, 100%, and 95.45%, respectively, for the detection of moderate to severe OSA [26]. Convolutional Neural Network (CNN) models applied to single-lead ECG data exhibit high precision in OSA detection, indicating them as reliable screening instruments [26].

Utilising ai in diagnosing insomnia and narcolepsy: AI has emerged recently as a prominent approach for diagnosing narcolepsy, a chief disorder of hypersomnolence apparent by unwarranted daytime sleepiness. Diagnosing narcolepsy typically includes an overnight PSG followed by a Multiple Sleep Latency Test (MSLT), method that is both time-consuming and laborious due to requirement of manual data scoring [27]. AI may help address this challenge through the automation analysis, enabling rapid and efficient diagnosis.

Recent literature suggests development of automated classifiers utilising single-channel EEG to distinguish between sleep and wake epochs. Results indicate that individuals with narcolepsy type-1 represent a significantly greater frequency of sleep-wake transitions during the night compared to both narcolepsy type-2 patients and normal controls [8]. Linear discriminant analysis has been utilised to extract and integrate features from EOG, EMG, and EEG recordings, resulting in multidimensional sleep state space projections that effectively distinguish narcolepsy type-1 from controls by leveraging the unique sleep state dissociation observed in affected patients [18].

Additionally, DL approaches have enhanced this process. The generation of hypnodensity graphs from PSG recordings enables CNN to probabilistically present sleep stages, effectively capturing subtle transitions that are highly predictive of narcolepsy type-1, achieving sensitivities of 91% and specificities of 96% [28].

Insomnia: AI is progressively used to diagnose and manage insomnia, offering new remedies that exceed conventional methods. Initial studies utilised Singular Spectrum Analysis (SSA) of sleep EEG signals to distinguish among paradoxical insomnia, psychophysiological insomnia, and control groups [8]. In 2016, Ramiro CV et al., introduced a three-stage model that integrates Time Varying Autoregressive Moving Average (TVARMA) preprocessing, a fuzzy inference system for hypnogram creation, and logistic regression to differentiate insomnia patients based on similarity distances [29].

Subsequent research enhanced this domain by training deep neural network classifiers using EEG data. These networks, using features extracted from one or two EEG channels, achieved discrimination accuracies of up to 92% with dual channels and 86% using a single channel compared to manual scoring [22]. In parallel, researchers have explored non PSG data sources; natural language processing has been applied to Twitter messages to extract associations involving stress, headache, and insomnia, while unsupervised learning on wearable data identified five clusters of insomnia activity [8].

AI In Sleep Disorder Management

Remote monitoring and telemedicine: Remote Patient Monitoring (RPM) employs electronic technologies to collect and transmit health data continuously. RPM systems use wearable sensors and contactless strategies to screen essential signs, involving heart rate, respiratory rate, blood pressure, and oxygen saturation. Integrating AI has improved prognostic abilities through ML and DL algorithm application for identifying early deviations in functional parameters [28]. AI-powered systems deliver real-time, tailored management strategies by deliberating individual characteristics and medical histories, offering timely warnings contributing to compact hospitalisation and improved clinical outcomes [22].

Telemedicine has established efficacy in diagnosing and managing sleep disorders, including OSA, insomnia, REM, sleep behavior disorders, and other sleep-associated conditions. Remote consultations and tele-monitoring of CPAP therapy, have improved treatment adherence, symptom control, and patient accessibility to specialised sleep care [30]. Additionally, access to behavioural conduct, including CBT-I, has been extended with literature suggesting that CBT-I and brief behavioural therapy delivered remotely are equivalent to in-person treatment [30]. Given the limited availability of behavioural sleep specialists, digital CBT-I programs have revealed efficiency in improving sleep quality [31]. Among children and adolescents, telehealth follow-ups and CBT-I has been demonstrated effective in managing OSA and insomnia [30].

AI-guided cognitive behavioural therapy for insomnia (CBT-I): CBT-I is a multimodal and structured strategy specifically designed for insomnia, combining cognitive re-structuring with behavioural modalities for enhancing sleep quality and efficacy [31]. Patients with insomnia and without psychiatric co-morbidities revealed significant improvement in insomnia severity, with smaller sleep latency and improved daytime symptoms with CBT-I [29]. Despite its status as the gold standard, CBT-I implementation faces several limitations including patient acceptance due to limited awareness regarding CBT-I, leading to less engagement and restricted trained psychotherapists particularly in resource-limited regions further constraining access [31].

With the advancement in digital therapies and technologies, eCBT-I have emerged as a non pharmacological intervention based on conventional CBT which leverages digital tools, internet platforms and mobile applications to overcome geographical barriers and limited service availability for remote delivery and self-management [32]. However, eCBT-I is limited by lack of digital skills among patients to utilise platforms effectively in addition to face-to-face interaction which increase the likelihood of treatment interruption [32]. For improving accessibility and affordability, AI has accelerated transition from structured eCBT-I to AI-guided CBT-I methods [32]. In 2009, Ritterband et al. developed an algorithm providing personalised sleep-restriction recommendation through email reminders and multimedia content, with advantages at six months follow-up [33].

Mobile applications have emerged recently with Horsch CH et al., utilised sleepcare tool, which involved sleep diary, meditation exercises, and sleep hygiene recommendations, thereby, improving insomnia symptoms and sleep efficiency [34]. Moreover, Werner-Seidler A et al., proposed Sleep Ninja for young adults which included game-like features and assist in alleviating insomnia and concomitant depression within 6-14 weeks of application [35].

Although advancements have been made, entirely automated programs still lack the interactive depth of in-person therapy. As users input sleep data and access educational resources, their personal concerns and engagement are not addressed. To overcome this, an AI-guided digital coach was developed which engaged patients daily with routine sleep diaries and delivered CBT-I knowledge [36]. Furthermore, Shim H et al., developed a conversational AI analysing free-text to identify insomnia causes and impacts [37]. Similarly, Rick SR et al.,'s chatbot, SleepBot, uses natural language processing to promote sleep hygiene via texts [38]. Moreover, Shuti, a sleep intervention modality generated by Microsoft, provided AI-guided CBT-I to users with personalised sleep management suggestions for analysing their sleep patterns and improving insomnia symptoms [39]. Similarly, SleepScore is asleep health app that combines CBT-I principles and AI analytics to assist users improve their sleep quality by tracking sleep patterns and behavioural data [40]. Beyond personalisation, AI-integrated CBT-I heralds new eras in scalability and treatment accessibility for sleep disorders. CBT-I Coach developed by United States Department of Veteran Affairs assists users in managing insomnia on their own by integrating CBT-I principles and delivers personalised treatment plans by collecting users sleep logs and mood data [41]. Notably, in 2020 the Food Drug Administration (FDA) approved Somryst, a prescription digital therapeutic that delivers CBT-I via a mobile application to tailor therapy on an individual basis in real-time [42]. Sleepio is a CBT-I based digital sleep treatment tool that utilised AI for analysing user's sleep data and providing personalised sleep interventions based on user's feedback based on behavioural, emotional state and sleep patterns of users to improve their sleep quality [43]. Tools such as Calm and Headspace combines meditation and CBT-I technology to provide users with personalised sleep quality improvement and insomnia symptom reduction recommendations through AI analysing sleep data, mood swings, meditation feedback and emotional states [44,45].

RECENT ADVANCES AND EMERGING TECHNOLOGIES

Machine Learning and Deep Learning Models

AI tools function prominently in sleep staging and sleep disorders diagnosis. The ML and DL algorithms have markedly improved the efficiency and accuracy of OSA detection and classification. For instance, Sleep EEG Net utilises DL approach and attained a precision of 84.26% in sleep stage scoring [46]. Similarly, several algorithms including random forest, K-nearest neighbor, and Support Vector Machine (SVM) gained accuracy of 87.4% in sleep stage categorisation [47]. Furthermore, AI models assist in detecting sleep disorders. For instance, ML algorithms, such as Random Forests (RF), CNN and SVMs, have shown significant precision in determining sleep apnoea clinical metrics like AHI from single EEG recordings [48]. Another sleep-controlling model for OSA detection uses a CNN-Long Short Term Memory (LSTM) structure on single-channel ECG signals, attained 96.1% sensitivity, 96.1% precision, and 96.2% specificity on the Apnoea-ECG dataset [49]. An ML model employing dual-accelerometry system for airflow estimation attained an accuracy of 89% in predicting the AHI. An RF-based model that combined wearable respiratory effort and SpO_2 signals achieved optimal performance in AHI estimation. DL models depict significant competence in analysing time-series data. A deep Bi-directional LSTM (BiLSTM) model effectively identified OSA events from nasal pressure inputs, whereas a CNN framework demonstrated high accuracy in detecting OSA in specific populations, including post-stroke patients [26]. Furthermore, Wara et al. in a systematic review reported that neural network algorithms were having 47% of usage for sleep disorder detection along with LSTM, SVM, RF, and ensemble learning accounting for 15%, 7%, 6%, and 12% of usage, respectively with accuracy of 86.42%, specificity of 30.86%, and sensitivity of 29.63% [48]. Urtnasan E et al., proposed an AI-based algorithm namely sleep disorder network for sleep disorders using deep neural networks which can extract and evaluate the complex cyclical rhythms of sleep disorders affecting ECG patterns. The authors proposed algorithm for automatic sleep disorder classification based on single-lead ECG and attained F1 scores between 95% to 99% for sleep disorders [9].

Hybrid models that integrate various techniques have been investigated. SVM models achieved over 97% accuracy in classifying normal and apnoea-related waveforms. When combined with RF, the average sensitivities and specificities were 82% and 78%, respectively [50]. Recently, DL-based approaches using non intrusive signals, involving variable heart rate, photoplethysmography, and respiratory energy, have depicted sensitivities and specificities between 77-91% and 75-89%, respectively [50,51].

Integration of AI with Internet of Medical Things (IoMT)

Integrating AI with IoMT is reforming sleep disorder management and enabled continuous and remote management of physiological constraints along with early identification of sleep disorders including OSA, REM sleep behaviour disorder, and insomnia through wearable devices and smart sensors. These massive support systems serve as the raw input for advanced AI algorithms, remote clinician oversight, and individual therapy modifications like CPAP optimisation that perform sleep staging and anomaly detection, resulting in timely diagnostics and improved long-term patient care [50].

A marked example is Pulse2AI system, that standardised wearable pulsatile sensor data for enhancing precision of remote health valuations. This method aids in empowering doctors when integrated into an IoMT setting and offered real-time and multi-dimensional data by facilitating rapid detection and continuous management of sleep disorders [52].

Azman N et al. created an IoMT tele-insomnia system that uses continuous sensor data to track nocturnal activities and determine unusual sleep patterns in insomniacs [53]. Similarly, IoMT-based methods can identify rapid signs of sleep apnoea and other associated disorders by subtly recording mobility and postural information while sleeping [53]. Nevertheless, limitations of data privacy, appliance compatibility, and sensor information standardisation still remains [18].

ETHICAL AND LEGAL DELIBERATIONS OF AI IN SLEEP MEDICINE

As AI has emerged across several domains, it brings out numerous ethical and legal issues that must be addressed. ML is highly dependent on high-quality data, but acquiring good data often stands in contrast to considerations for patient privacy, limiting regulations and varying institutional policies [54]. Additionally, utilising data collection systems from different Institutions create significant hurdles in achieving interoperability and data standardisation, thereby increasing the risk of breaches when integrating information from multiple sources.

For promoting AI progression in clinical field, legal shield for researchers is essential for protecting them from potential obligations. Baseline datasets are essential for evading biases in AI algorithms.

Current datasets lack certain populations like minor individuals, contributing to biased consequences and limited AI utility in such AI communities [28]. Professional administrations namely AASM have explained AI committees for supporting best practices, while regulatory bodies including FDA continually assess these methods from safety perspective [6].

Regulatory Guidelines

For safely integrating AI into sleep disorder management, regulatory standards and clinical validation are essential. The World Health Organisation (WHO) developed a digital innovation framework emphasising on AI tool assessment focusing their advantages, hazards, viability, adequacy, resource necessities, and equity [55]. The procedures are intended to facilitate universal health coverage and healthcare system improvement.

Ethical considerations play an important role in the development of AI in medicine, highlighting the importance of human dignity, autonomy, justice, and transparency. European regulatory bodies have recognised risk-based categorisation for AI tools, necessitating applications distressing fundamental rights, involving data privacy, undergo comprehensive evaluation for establishing oversight procedures [56].

In sleep medicine, clinical validation of AI models requires extensive, wide datasets accounting for variability in sleep patterns impacted by parameters including age and night-to-night differences [42]. Randomised controlled trials and independent authentications are important for confirming the safety and efficacy of AI tools. Reporting standards like Consolidated Standards of Reporting Trials–AI (CONSORT-AI) and Standard Protocol Items: Recommendations for Interventional Trials–AI (SPIRIT-AI) endorses methodological consistency, aligning AI methods with conventional clinical trial standards [57].

CHALLENGES AND FUTURE DIRECTIONS

Technical Barriers

ANNs improves the identification of complex, non linear linkage among variables associated with OSA risk, thus increasing diagnostic accuracy. A significant restriction of such models is absence of transparency. In contrast to traditional statistical methods like logistic regression, which provide explicit and interpretable relationships between variables, ANNs function as “black boxes.” The input and output variables are recognisable; however, the internal decision-making processes, including the weighting and interaction of specific variables, remain obscure. Opacity obstructs the capability to trace or clarify the model’s conclusion procedure. There exists a trade-off between predictive performance and model interpretability: highly accurate models, such as DL, tend to be less transparent, whereas simpler models like linear regression provide greater interpretability but lacks precision. For ANNs to be effectively utilised in OSA diagnosis, the improvement in accuracy must surpass the concerns regarding their lack of explainability [28].

Data and biases

One of the key challenges for the use of AI in sleep disordered breathing diagnosis, including OSA, is the quality of the datasets included in training and validating the model. A lack of completeness or appropriate skewing in the dataset used can degrade diagnostic performance and limit clinical use [37].

Limited access to large datasets and difficulties of long-term data archiving also constrain model generalisability. Numerous models are developed using specifically delineated populations. Kirby SD et al., developed a model utilising data from a sleep clinic cohort characterised by a high prevalence of OSA (69%). In contrast, another system excluded younger individuals and those with low Body Mass Index (BMI) who did not snore [58]. The limitations of such training diminish the reliability of AI tools for widespread public screening, even when data from the general population is utilised initially [59]. Biases connected with age, sex, and other social determinants may concede with AI models. The incidence of OSA is analogous globally; although, certain populations, involving older adults, racial minorities, and entities with obesity, displayed increased burdens. Incorporating varied, localised information, while reducing dependency on self-reported inputs improved model robustness and reduce bias [60].

AI in Personalised Sleep Medicine

AI-driven predictive models have been developed to determine persons at risk of OSA, using vital interpreters including age, sex, and BMI, depicting significant precision. Analysing large datasets through AI algorithms, identifying intricate tendencies associated with patient features, sleep physiology, and treatment retorts, thereby permitting precise OSA phenotyping and endotyping [18]. Chief features including upper airway collapse, reduced muscle receptiveness, lessen arousal thresholds, and irregular ventilatory management were analysed [18].

Furthermore, ML models depict consequences connected with distinct strategies; for instance, certain algorithms predict long-term effectiveness of oral applications and CPAP therapy. Recent ISAACC trial, have identified subgroups of OSA patients exhibiting diverse responses to continuous positive CPAP which may result in a reduced incidence of cardiovascular events in patients with shorter apnoea durations relative to prolonged events [61].

Furthermore, diagnosis and management matching, AI-driven prognostic evaluations have improved OSA severity assessments. Advanced ML strategies incorporated ventilatory division histograms alongside parameters including hypoxia burden and arousal metrics offering a comprehensive understanding of the disorder [26]. Similar strategies are currently being examined in various sleep disorders and in chronotherapy, where AI aids in aligning treatment schedules with individual circadian rhythms to enhance efficacy and reduce toxicity.

Advancing Sleep Medicine Through AI-driven Integration of Big Data

The integration of AI and ML with big data presents considerable potential for advancing research and improving clinical care in sleep medicine. Model efficiency is prominently influenced by dimensions, quality and choice of training datasets. Insufficient or non representative data may result in overfitting or underfitting, thereby diminishing the model’s capacity to generalise to new patient populations [26].

Scientists should arrange using broad and varied datasets precisely representing vast population to overcome hurdles. Utilising random sampling methods and training iteratively with assessment are vital for facilitating reliable model creation. Resources including the National Sleep Research Resource (NSRR) and the U.K. Biobank permit accessibility wide-ranging sleep-associated datasets, ensuring global research initiatives [62]. The Human Sleep Project pursues allocating wide-ranged real-time sleep data digitally, improving understanding of sleeping patterns and associated etiological factors [63].

Limitation(s)

The included studies showed heterogeneity in study design, AI models, datasets, and outcome measures, limiting direct comparison. Several studies were based on small datasets or controlled settings, which may affect generalisability to real-world clinical practice. Additionally, rapidly evolving AI technologies may result in emergence of newer evidence beyond the review period. Since this was a comprehensive review, quantitative synthesis was not performed.

CONCLUSION(S)

Integrating AI for sleep disorders management has significantly transformed clinical care. Conventional platforms including PSG data could be automated using ML and DL algorithms along with precise detection of sleeping disorders including OSA, insomnia, and narcolepsy. Furthermore, personalised treatment can be facilitated by these tools, addressing the inadequacies of conventional and laborious strategies. Incorporation of wearable sensors and the IoMT enables real-world data attainment and remote healthcare distribution. Nevertheless, challenges exist associated with data privacy, normalisation, interoperability and constrained admittance to wide-ranged, high-quality datasets, demanding cooperative efforts among healthcare providers, scientists and regulatory bodies.

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