BIOSCIENCES BIOTECHNOLOGY RESEARCH ASIA, March 2025. Vol. **22**(1), p. 103-112

Role of Artificial Intelligence in Paediatric Sleep Medicine

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http://dx.doi.org/10.13005/bbra/3344

(Received: 07 December 2024; accepted: 17 March 2025)

Pediatric sleep apnea, including obstructive sleep apnea (OSA) and central sleep apnea (CSA), can severely affect a child's physical health and cognitive function. Traditionally, polysomnography (PSG) has been the gold standard for diagnosis, but its high cost, invasiveness, and difficulty in pediatric use present significant challenges. Advances in Artificial Intelligence (AI) and Machine Learning (ML) are now offering transformative solutions, enhancing diagnostic accuracy, personalizing treatments, and increasing accessibility. AI-powered home sleep apnea tests (HSATs) provide a non-invasive alternative by analyzing key physiological signals such as oxygen saturation (SpO_2), electrocardiograms (ECG), and nasal airflow pressure (NAP) to detect apneic events and assess severity. These AI-driven tools offer greater convenience compared to traditional PSG. Additionally, ML models show promise in predicting adherence to therapies like positive airway pressure (PAP) for OSA, while advanced AI algorithms are improving CSA detection by analyzing complex physiological patterns more effectively. Cutting-edge innovations, including transformer models and edge AI, are enabling real-time sleep staging tailored management, making diagnostic tools more efficient and widely available. By integrating AI-driven solutions, healthcare providers can offer earlier and more accurate diagnoses, leading to timely interventions that improve long-term health outcomes for children. Despite these advancements, further validation through large-scale clinical studies is necessary to establish AI's reliability across diverse pediatric populations. With continued research and refinement, these technologies could become standard tools for detecting and managing pediatric sleep apnea, paving the way for a future where diagnosis is more accessible, cost-effective, and child-friendly.

Keywords: Artificial intelligence (AI), Convolutional neural networks (CNNs), Central sleep apnea (CSA), Machine learning (ML), Obstructive sleep apnea (OSA), Pediatric sleep apnea, Polysomnography (PSG).

Sleep apnea in children, particularly obstructive sleep apnea (OSA) and central sleep apnea (CSA), is a significant health concern that can have profound effects on both physical health and cognitive development. These conditions are characterized by repeated interruptions in breathing during sleep, leading to oxygen desaturation and frequent awakenings.

Polysomnography (PSG) remains the gold standard for diagnosing sleep disorders but has several limitations. It is costly and resource-intensive, limiting accessibility and creating a demand for cost-effective alternatives like home sleep testing.[1,2] The requirement for an overnight stay in a clinical setting disrupts natural sleep patterns, making it inconvenient for patients.[3]

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Additionally, PSG interpretation remains complex and requires skilled specialists, posing challenges in clinical integration.[4] While effective, PSG may not always be necessary, as home respiratory polygraphy has been shown to be an equally viable diagnostic alternative for certain conditions.[5]

In recent years, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful tools in the field of sleep medicine, offering innovative solutions to overcome the limitations of traditional diagnostic methods. AI algorithms, particularly those based on deep learning, have shown remarkable potential in analyzing complex physiological data to detect sleep apnea with high accuracy. These technologies can process large datasets, identify patterns, and make predictions that are often beyond the capability of human clinicians.[6,7]

One of the most promising applications of AI in pediatric sleep medicine is the development of home sleep apnea tests (HSATs). These tests leverage AI-powered devices to monitor key physiological signals such as oxygen saturation (SpO_2), electrocardiogram (ECG), and nasal airflow pressure (NAP) in the comfort of the patient's home. HSATs are not only more convenient but also more cost effective than traditional PSG, making them an attractive alternative for diagnosing sleep apnea in children.[8,9]

AI and ML are also revolutionizing the way sleep apnea is treated. By analyzing large datasets, AI algorithms can predict the most effective treatment options for individual patients, whether it be positive airway pressure (PAP) therapy, surgical intervention, or lifestyle modifications. This personalized approach ensures that children receive the most appropriate treatment, thereby improving their overall health outcomes.[10,11]

Moreover, AI is playing a crucial role in the development of non-invasive, contactless monitoring systems that can accurately track sleep-related parameters without the need for physical sensors. These systems use advanced algorithms to analyze data from wearable devices, such as smartwatches, to detect sleep apnea and other sleep disorders. This approach not only enhances patient comfort but also enables continuous monitoring, which is particularly beneficial for children with chronic sleep issues.[12,13]

Despite these advancements, there are still challenges that need to be addressed. One of the primary limitations is the lack of large, diverse datasets for training AI models. Most existing datasets are derived from adult populations, and there is a significant gap in pediatric-specific data. This limits the generalizability of AI models to children, whose physiological responses and sleep patterns differ significantly from those of adults.[14,15]

This review explores how AI is transforming the diagnosis and treatment of pediatric sleep apnea, making it more accurate, affordable, and accessible for families.

MATERIALS AND METHODS

A comprehensive search was conducted across PubMed, Scopus, and Web of Science, focusing on studies published between 2013 and 2024. Relevant keywords and MeSH terms related to AI, machine learning, pediatric sleep apnea, and polysomnography were used. The inclusion criteria encompassed peer-reviewed studies evaluating AI-based diagnostics and treatment approaches in pediatric sleep apnea. Non-English studies and adult-focused research were excluded. A total of 50 studies were initially retrieved. After removing 12 duplicates,38 studies underwent title and abstract screening. Following a full-text review, 28 studies were deemed eligible for inclusion based on methodological quality and relevance. These studies were categorized based on AI models used, input data, and performancemetrics. A structured qualitative synthesis was performed to summarizeadvancements and challenges in AI-based pediatric sleep medicine,ensuring reproducibility and clinical relevance.

RESULTS

Sleep apnea

Pediatric sleep apnea is a significant health concern, affecting approximately 1% to 5% of children in the United States. If not addressed promptly, it can lead to various physical and mental health complications. Unlike adults, pediatric sleep apnea presents with distinct clinical causes and characteristics. Despite extensive research on adult sleep apnea, the investigation into pediatric sleep apnea remains relatively limited.[8]

Prediction of Sleep apnea by Artificial intelligence

Artificial intelligence (AI) is increasingly being recognized for its ability to enhance the diagnosis and management of pediatric sleep apnea. By analyzing large datasets, AI can uncover patterns linked to obstructive sleep apnea (OSA), predict treatment adherence, and tailor management plans. For example, AI-driven algorithms can improve screening processes by identifying at-risk children based on their clinical features, enabling earlier interventions.[6] Additionally, AI technologies have shown promise in developing non-invasive, contactless systems that accurately monitor sleep-related parameters, offering an alternative to traditional polysomnography. As AI continues to evolve in pediatric sleep medicine, it has the potential to revolutionize how doctors diagnose and treat the condition, leading to better outcomes for children with obstructive sleep apnea.[6,7]

Types of Sleep apnea

Sleep apnea is a sleep disorder characterized by repeated interruptions in breathing during sleep. The two most common types are obstructive sleep apnea (OSA) and central sleep apnea (CSA).

Obstructive sleep apnea

Pediatric obstructive sleep apnea (OSA) is marked by repeated episodes of breathing cessation (apneas) and partial reductions in airflow (hypopneas). These interruptions result in drops in oxygen levels and frequent awakenings, leading to disrupted and restless sleep. Polysomnography (PSG) is considered the gold standard for diagnosing obstructive sleep apnea (OSA) in children. This test involves having children spend the night in a specialized sleep center, where up to 32 different biomedical signals are monitored and recorded.[16]

Convolutional Neural Networks (CNNs) in Pediatric OSA Diagnosis

A groundbreaking study explored the use of Convolutional Neural Networks (CNNs) to enhance the diagnostic accuracy of oximetry in detecting pediatric obstructive sleep apnea (OSA). The study utilized a large dataset of 3,196 blood oxygen saturation (SpO,) signals from children, training the CNN on 20-minute segments of this data to predict apneic events. This allowed for the calculation of the apnea-hypopnea index (AHI) for each subject, which is crucial in determining the severity of OSA.[17]

Performance of CNN Models

CNN outperformed traditional diagnostic methods, such as the 3% oxygen desaturation index (ODI3), and conventional machine learning approaches like multilayer perceptrons (MLP). Specifically, the CNN achieved higher Cohen's kappa values, a statistical measure of agreement, across various test datasets. This indicated that the CNN model provided better alignment with clinical diagnoses of OSA severity, making it a promising tool for improving diagnostic precision.

Machine Learning Algorithms for OSA Diagnosis

In addition to CNNs, various other machine-learning algorithms have been applied

Table 1. Summary of AI Models Used in Pediatric Sleep Apnea Diagnosis and Management

AI Model	Input Data	Key Features	Performance Metrics	Reference
Convolutional Neural Networks (CNNs)	SpO, signals (oximetry data)	Detects apneic events, calculates AHI	Higher Cohen's kappa than traditional methods	17
Support Vector Machines (SVM)	Brain diffusion tensor imaging	Classifies OSA severity	Accuracy: 77%	18
Random Forest (RF)	Clinical history, PSG data	Identifies OSA cases	Accuracy: 73%	18
Transformer-based Model	ECG, SpO, data	Home-based pediatric sleep apnea detection	AUROC: 90%, F1-score: 83.1%	8
LSTM-based Sleep Staging Model (CSleepNet)	Single-channel EEG	Edge AI for real-time sleep analysis	Accuracy: 83.06% (pediatric dataset)	25

to improve the screening and diagnosis of OSA in children. For instance, studies have shown that models like Support Vector Machines (SVM), Random Forests (RF), and Extreme Gradient Boosting (XGBoost) can accurately classify OSA cases from healthy controls. These models are trained on diverse datasets, including clinical history and polysomnography results.[10,11]

Performance of Other Machine Learning Models

In one study, the SVM model achieved an accuracy of 77% in classifying OSA severity based on brain diffusion tensor imaging data.[18] The Random Forest model showed a slightly lower accuracy of 73% but still provided valuable insights for identifying OSA severity. These models have proven beneficial in early clinical diagnosis, facilitating timely intervention for children at risk of severe sleep-disordered breathing.

Integration with Physiological Signals

While much of the focus has been on using SpO_2, signals for OSA diagnosis, there is significant potential for improving diagnostic accuracy by integrating additional physiological signals, such as airflow and electrocardiogram (ECG) data. By combining multiple data sources, these models can offer a more comprehensive assessment of sleep-disordered breathing. This approach would enhance the ability to differentiate between various levels of OSA severity, leading to better-targeted treatment and management strategies.[9,14]

The integration of machine learning, especially through convolutional neural networks (CNNs) and other advanced algorithms, marks a revolutionary shift in the diagnosis of pediatric obstructive sleep apnea (OSA). By utilizing deep learning techniques to analyze oximetry data and various other physiological signals, these models enable clinicians to achieve significantly higher diagnostic accuracy. What's even more impressive is that these methods are less invasive than traditional polysomnography (PSG), offering a more comfortable and efficient alternative for both patients and healthcare providers.

Predictive Modeling with Clinical Features

A study was conducted by using machine learning (ML) to predict the severity of pediatric obstructive sleep apnea (OSA) based on easily accessible clinical features. The researchers aimed to create a model that could accurately classify OSA severity, as determined by the apnea-hypopnea index (AHI), without the need for traditional and more invasive polysomnography (PSG).

The dataset used in this study consisted of clinical data from children who were suspected of having OSA. The team applied several machine learning algorithms to predict the AHI thresholds, which are critical for diagnosing the severity of OSA in pediatric patients. These thresholds help clinicians determine whether a child is experiencing mild, moderate, or severe sleep apnea, which directly impacts treatment decisions.

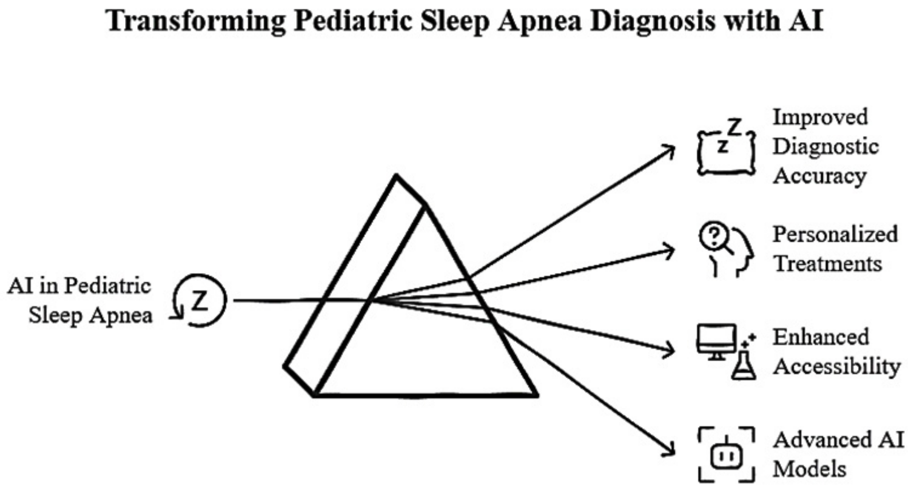

Fig. 1. Transforming Pediatric Sleep Apnea Diagnosis with AI

Model Performance and Impact

The results of the study were promising. The machine learning models demonstrated the ability to predict AHI thresholds with high accuracy, making this approach a practical alternative to PSG. By relying on clinical features that are readily available—such as medical history, physical examination findings, and basic physiological data—this predictive modeling technique simplifies the diagnostic process.[7]

Moreover, the use of machine learning in predicting OSA severity allows for earlier identification of children who may be at risk. Early intervention can significantly improve treatment outcomes and prevent the potential long-term complications associated with untreated OSA, such as growth delays, learning difficulties, and cardiovascular problems.

Central sleep apnea

Central sleep apnea (CSA) occurs when there is a failure to initiate breathing during sleep, leading to inadequate ventilation and disrupted gas exchange. Unlike obstructive sleep apnea (OSA), where breathing efforts continue despite blocked airways, central apnea is marked by a complete absence of respiratory effort during episodes of halted airflow. However, the distinction between the two conditions can sometimes be blurry, as there is significant overlap in their causes and effects. Similar to OSA, CSA can result in serious complications, such as frequent awakenings during the night, excessive daytime drowsiness, and a heightened risk of cardiovascular issues.[19]

Central Apnea Detection in Premature Infants Using Machine Learning

Central apnea, especially in premature infants, is a serious condition that can result in significant health complications if left unaddressed. Early and accurate detection of central apnea (CA) is crucial for prompt intervention, particularly in neonatal intensive care units (NICUs), where infants are more vulnerable. Timely recognition of CA can help prevent further health issues and ensure that affected infants receive the appropriate care to support their respiratory and overall health.[20]

Artificial Intelligence in Diagnosis

Artificial Intelligence (AI) and Machine Learning (ML) have shown great potential in enhancing diagnostic accuracy for central sleep apnea (CSA). These technologies can process complex data from polysomnography (PSG) more efficiently than traditional methods. For instance, ML algorithms can analyze physiological signals, such as oxygen saturation and respiratory patterns, to identify central apneas with greater precision.

1. Predictive Modelling: Machine learning models can be trained using features extracted from PSG data to predict the occurrence of CSA. By learning from historical data, these models can recognize patterns linked to central apneas, enabling earlier diagnosis and more timely interventions.

2. Enhancing Diagnostic Criteria: AI can play a key role in refining the diagnostic criteria for CSA by analyzing large datasets to establish more accurate thresholds for central apnea indices. For example, research suggests that a central apnea index (CAI) exceeding five events per hour should be considered abnormal and potentially indicative of CSA.[21,22]

The use of artificial intelligence (AI) and machine learning (ML) in predicting and diagnosing central sleep apnea (CSA) in pediatric populations marks a significant breakthrough in pediatric sleep medicine. By harnessing complex datasets from polysomnography and other physiological metrics, these technologies can greatly improve diagnostic accuracy. This not only aids in identifying CSA more efficiently but also supports timely interventions, ensuring that affected children receive the necessary care as early as possible.

Home based diagnostic test

Obstructive Sleep Apnea Hypopnea Syndrome (OSAHS) is a sleep-related breathing disorder that affects 1–5% of children with most prevalence between 2 and 8 years old.[23] If left untreated, it can lead to growth issues, behavioral problems, cardiovascular complications, and cognitive impairments. The diagnosis of OSAHS in children traditionally requires in-lab polysomnography (PSG), which is costly, time-consuming, and intrusive. This study introduces a machine-learning-based approach to address these challenges, offering a more accessible, at-home diagnostic method.

Existing AI diagnostic methods for OSAHS focus heavily on adult populations,[12,13,15,24] while pediatric OSAHS remains underexplored.

This study addresses the gap by designing a novel transformer-based machine learning model for pediatric OSAHS detection. Unlike prior studies that rely on extensive PSG signals, this work demonstrates the feasibility of using just ECG and SpO2 signals for effective diagnosis, which are easier to collect in home settings.

The study aimed to develop a simplified diagnostic tool for pediatric OSAHS, comparable in performance to PSG, but accessible for home use. Researchers used two large pediatric datasets: the Nationwide Children's Hospital (NCH) Sleep Data Bank and the Childhood Adenotonsillectomy Trial (CHAT). The proposed method involves a customized transformer architecture that processes multi-modal data from PSG, segmenting it into manageable epochs for analysis. Performance was evaluated using multiple signal combinations, emphasizing ECG and SpO2 to explore practical home-testing options.

The model outperformed existing methods, achieving an F1-score of 83.1% and an AUROC (area under the receiver operating characteristic curve) of 90% on the CHAT dataset. Importantly, using only ECG and SpO2 signals produced results close to those achieved with the full polysomnography setup, showing great promise for simplifying diagnostics. The findings suggest that pediatric OSAHS can be effectively detected with non-invasive, home-friendly methods, reducing reliance on expensive, clinic-based PSG.[8]

However, performance was slightly lower in younger children, emphasizing the need for age-specific model adjustments. The omission of EEG signals, which are crucial for detecting arousals and hypopneas in some pediatric cases, could limit its applicability in more complex scenarios. Additionally, the reliance on lab-quality data raises concerns about generalizability to wearable or home-device data, which may contain more noise.

Sleep staging models

Sleep staging involves classifying different phases of sleep, including Wake (W), Rapid Eye Movement (REM), and Non-Rapid Eye Movement (NREM), into distinct stages like N1, N2, and N3. Accurate sleep staging is crucial for diagnosing sleep disorders such as insomnia and obstructive sleep apnea (OSA). Despite advances, most automatic sleep staging methods cater to adults, leaving a gap in tools suitable for children, whose EEG patterns differ significantly.

A study addresses this gap by proposing CSleepNet, a lightweight automatic sleep staging method for children using single-channel EEG integrated with edge artificial intelligence (AI). Unlike traditional cloud-based approaches, this method operates on edge devices, enhancing privacy, reducing bandwidth usage, and allowing real-time sleep analysis. The study aims to develop a robust, resource-efficient sleep staging model tailored for children. It also seeks to validate the model's performance across multiple datasets. Using a combination of 1D convolutional neural networks (1D-CNN) and long short-term memory (LSTM), CSleepNet processes raw EEG data without manual feature extraction. The model achieved 83.06% accuracy and 76.50% F1-score on a pediatric dataset and 86.41% accuracy on the Sleep-EDFX dataset, validating its effectiveness. Logcosh loss function outperformed alternatives, ensuring optimal training.[25] Challenges such as misclassification in transitional stages (e.g., N1) and noise from pediatric EEG were identified. The edge AI approach proved effective for deployment on portable devices like smartphones, improving accessibility. While achieving high accuracy and efficient deployment, the study highlights data scarcity and difficulties in classifying transitional stages as key limitations. This study is a significant step toward child-specific sleep monitoring, with plans to enhance loss functions and expand datasets for broader applicability.

Prediction modeling

Pediatric obstructive sleep apnea (OSA), which affects 6–9% of children. Traditional diagnosis relies on in-laboratory polysomnography (PSG), a complex and resource-intensive process. This study bridges a critical gap by proposing the use of nasal air pressure (NAP) signals and machine learning models to classify specific respiratory events and predict the anatomical site of obstruction. This novel approach, focusing on single-channel data, simplifies the diagnostic process and holds the potential to reduce reliance on invasive methods like drug-induced sleep endoscopy (DISE).The transformation of pediatric sleep apnea diagnosis with AI is depicted in Figure 1.

The primary aim was to develop a machine learning model that could classify sleep events as normal breathing, obstructive hypopnea, obstructive apnea, or central apnea using NAP signals obtained during PSG. The secondary objective was to predict the site of obstruction, either adenotonsillar or tongue base, based on hypopnea event data. The study included data from 28 pediatric patients aged 1–16 years. NAP signals were extracted and transformed into scalogram images, which were analyzed using deep learning models, such as ResNet-50. Model performance was evaluated through Monte Carlo resampling, and its accuracy was compared to that of board-certified pediatric sleep physicians.

The machine learning model achieved a mean classification accuracy of 70.0% for identifying sleep events, significantly outperforming clinicians, who averaged 53.8%. The model performed particularly well in identifying normal breathing and obstructive hypopneas but had challenges distinguishing certain events, such as central apneas. For predicting the site of obstruction, the model achieved an accuracy of 75%, with high sensitivity (78.1%) and specificity (72.1%). In a head-to-head comparison, clinicians were most accurate at identifying normal breathing (84.4%) but struggled with obstructive and central events. Across all event types, the machine learning model averaged a higher accuracy of 77.5%.[26]

The results underscore the feasibility of using NAP as a non-invasive diagnostic tool for pediatric OSA. This approach not only simplifies the diagnostic process but also offers actionable insights into anatomical obstruction sites, potentially guiding treatment strategies. However, the study has limitations. The sample size was small, limiting the generalizability of findings. The use of surgery as a proxy for anatomical obstruction may introduce bias, and reliance on single-channel NAP data might not capture the full complexity of sleep-disordered breathing. Furthermore, the study was conducted in a single tertiary care center, which may not represent broader patient populations.

Despite these limitations, the study represents a significant advancement in pediatric OSA diagnostics. It demonstrates that machine learning models can outperform clinicians in classifying respiratory events and predicting obstruction sites using minimal, non-invasive data. Future research should focus on validating these findings in larger and more diverse populations, incorporating additional data channels, and improving model accuracy for complex cases like central apneas. Ultimately, this approach could pave the way for accessible, scalable, and efficient diagnostic tools for pediatric sleep-disordered breathing.

Sleep problems and psychiatric disorders like ADHD are prevalent among children, often leading to significant neurocognitive and functional impairments. Current diagnostic methods heavily rely on subjective clinician evaluations, which are prone to variability and recall bias. This study addresses the need for objective, real-time diagnostic tools by leveraging wearable device data and machine learning (ML) models to predict ADHD and sleep problems. Using data from the Adolescent Brain Cognitive Development (ABCD) study, the researchers analyzed 21 days of wearable data from 5725 children, incorporating features such as circadian rhythms, sleep stages, activity levels, and heart rates. Light Gradient Boosting Machine (LightGBM) emerged as the best-performing model, achieving an AUC of 0.798 for ADHD and 0.737 for sleep problems. Key predictors included heart rate metrics for ADHD napping duration and sedentary activity for sleep problems. While the models demonstrated reasonable predictive performance and highlighted the potential of digital phenotyping for early screening, limitations such as data imbalance, wearable device inaccuracies, and high false-positive rates constrain their diagnostic applicability. Nonetheless, this study underscores the utility of integrating wearable technology and ML for early detection and intervention in children's mental health, paving the way for future research to refine these methods and improve their reliability.[27]

A summary of AI models used in the diagnosis and management of pediatric sleep apnea is provided in Table 1.

DISCUSSION

The field of pediatric sleep medicine is rapidly evolving with the integration of artificial intelligence (AI) and machine learning (ML). Two key emerging trends that hold great promise are federated learning and wearable AI technologies.

Federated learning is a decentralized AI approach that enables multiple institutions to collaboratively train models without sharing raw data. This technique enhances privacy and security, addressing concerns associated with centralizing sensitive pediatric health data. In pediatric sleep medicine, federated learning can improve diagnostic accuracy by integrating diverse datasets from multiple centers while ensuring patient confidentiality.[28]

Wearable AI technologies are also revolutionizing pediatric sleep monitoring. Advanced smartwatches, sleep bands, and wireless biosensors equipped with AI-driven algorithms can continuously monitor key physiological parameters such as oxygen saturation (SpO,), heart rate variability, and sleep stages.[29-31] These devices enable real-time detection of sleep disorders, reducing reliance on expensive and intrusive polysomnography (PSG). The development of edge AI further enhances wearable technology by enabling real-time processing on-device, minimizing latency and reliance on cloud-based computations. Future research should focus on improving the accuracy and generalizability of these models while ensuring their seamless integration into clinical workflows.While AI offers transformative potential in pediatric sleep medicine, its implementation raises several ethical concerns that must be addressed.

One major issue is data privacy. AI models rely on extensive patient data, making robust data protection mechanisms crucial to prevent unauthorized access and breaches. Federated learning presents a potential solution by allowing model training without directly sharing patient data, thereby enhancing privacy.[28]

Informed consent is another critical factor. Given that pediatric patients are involved, obtaining consent must extend beyond parents or guardians to include child-friendly explanations whenever possible. Transparent discussions regarding AI decision-making processes, data usage, and potential risks are essential to maintain trust in AI-driven healthcare.[32]

Additionally, bias in AI algorithms presents a challenge. AI models trained on limited or non-representative datasets risk perpetuating disparities in diagnosis and treatment recommendations. To mitigate this, researchers must ensure diverse and representative datasets, apply bias-detection techniques, and continuously validate AI models across various pediatric populations.[33]

Addressing these ethical concerns is imperative to ensure that AI enhances pediatric sleep medicine while maintaining fairness, accuracy, and patient-centric care.[34] By integrating federated learning, improving wearable AI capabilities, and prioritizing ethical considerations, the future of pediatric sleep medicine can achieve greater accessibility, accuracy, and equity in healthcare delivery.

CONCLUSION

Pediatric sleep apnea, including obstructive and central types, can lead to serious long-term health issues if untreated. However, advancements in artificial intelligence (AI) and machine learning (ML) are enhancing diagnosis and treatment. AI tools, such as convolutional neural networks (CNNs), improve diagnostic accuracy, while machine learning models utilize non-invasive signals like SpO, , ECG, and NAP to offer more accessible, cost-effective, and patient-friendly solutions, especially for home-based diagnostics.

These technologies simplify the diagnostic process and reduce the need for invasive procedures. Machine learning models, including predictive analytics and transformer-based approaches, make early intervention more feasible through wearable devices. Although challenges like data limitations and model generalizability remain, AI and ML have the potential to revolutionize pediatric sleep medicine by enabling earlier diagnoses and better outcomes. Future research should focus on refining these methods and ensuring their broad accessibility.

ACKNOWLEDGEMENT

We extend our sincere gratitude to J.K.K. Nattraja College of Pharmacy, Kumarapalayam, for their continuous support and resources throughout this project. Our heartfelt thanks to all collaborators and mentors who provided valuable insights and guidance during the preparation of this review article. Special appreciation goes to the institutions and individuals who contributed data, expertise, and time to enrich the content of this study.

Funding Sources

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Conflict of interest

The authors do not have any conflict of interest.

Data Availability Statement

This statement does not apply to this article.

Ethics Statement

This research did not involve human participants, animal subjects, or any material that requires ethical approval.

Informed Consent Statement

This study did not involve human participants, and therefore, informed consent was not required.

Clinical Trial Registration

This research does not involve any clinical trials**.**

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Not Applicable.

Author Contributions

Ashokkumar A: Contributed to data collection, literature review and drafting the manuscript; Venkateswaramurthy Nallasamy: Conceptualized and supervised the study, critically reviewed the manuscript, and provided guidance throughout the preparation process; Vidhya Lekshmi Krishnan: Assisted in the literature review, manuscript drafting, and formatting; Chitra Thara Sughumaran: Supported data analysis, reviewed the manuscript, contributed to refining the final draft.

REFERENCES

1. Hirshkowitz M. Polysomnography challenges. *Sleep Med Clin*. 2016;11(4):403-411.
2. Corral J, Sánchez-Quiroga M, Carmona-Bernal C, *et al*. Conventional polysomnography is not necessary for the management of most patients with suspected obstructive sleep apnea: Noninferiority, randomized controlled trial. *Am J Respir Crit Care Med*. 2017;196(9):1181-1190.
3. Boulos M, Jairam T, Kendzerska T, et al. Normal polysomnography parameters in healthy adults: A systematic review and meta-analysis. *Lancet Respir Med*. 2019;7(6):533-543.
4. Markun L, Sampat A. Clinician-focused overview and developments in polysomnography. *Curr Sleep Med Rep*. 2020;6(4):309-321.
5. Corral J, Sánchez-Quiroga M, Carmona-Bernal C, et al. Conventional polysomnography is not necessary for the management of most patients with suspected obstructive sleep apnea: Noninferiority, randomized controlled trial. *Am J Respir Crit Care Med*. 2017;196(9):1181-1190.
6. Verma RK, Dhillon G, Grewal H, Prasad V, Munjal RS, Sharma P, Buddhavarapu V, Devadoss R, Kashyap R, Surani S. Artificial intelligence in sleep medicine: Present and future. *World J Clin Cases*. 2023 Dec 6;11(34):8106-8110.
7. Qin H, Zhang L, Li X, Xu Z, Zhang J, Wang S, Zheng L, Ji T, Mei L, Kong Y, Jia X, Lei Y, Qi Y, Ji J, Ni X, Wang Q, Tai J. Pediatric obstructive sleep apnea diagnosis: leveraging machine learning with linear discriminant analysis. Front Pediatr. 2024;12:1328209.
8. Fayyaz H, Strang A, Beheshti R. Bringing At-home Pediatric Sleep Apnea Testing Closer to Reality: A Multi-modal Transformer Approach. *Proc Mach Learn Res*. 2023;219:167-185.
9. **Salari N, Hosseinian-Far A, Mohammadi M, *et al*.** Detection of sleep apnea using machine learning algorithms based on ECG signals: A comprehensive systematic review. *Expert Syst Appl*. 2022;187:115950.
10. Liu K, Geng S, Shen P, Zhao L, Zhou P, Liu W. Development and application of a machine learning-based predictive model for obstructive sleep apnea screening. *Front Big Data*. 2024;7:1353469.
11. Shi Y, Zhang Y, Cao Z, et al. Application and interpretation of machine learning models in predicting the risk of severe obstructive sleep apnea in adults. *BMC Med Inform DecisMak*. 2023;23(1):230.
12. Chen X, Chen Y, Ma W, Fan X, Li Y. Toward sleep apnea detection with lightweight multi-scaled fusion network. *Knowl-Based Syst*. 2022;247(108783):108783.
13. Zhao X, Wang X, Yang T, et al. Classification of sleep apnea based on EEG sub-band signal characteristics. *Sci Rep*. 2021;11(1):5824.
14. Han H, Oh J. Application of various machine learning techniques to predict obstructive sleep apnea syndrome severity. *Sci Rep*. 2023;13(1):6379. Published 2023 Apr 19. doi:10.1038/s41598-023-33170-7

15. Bozkurt F, Uçar MK, Bozkurt MR, Bilgin C. Detection of abnormal respiratory events with single channel ECG and hybrid machine learning model in patients with obstructive sleep apnea. *IRBM*. 2020;41(5):241-251.
16. Kaditis A, Kheirandish-Gozal L, Gozal D. Pediatric OSAS: Oximetry can provide answers when polysomnography is not available. *Sleep Med Rev*. 2016;27:96-105.
17. Vaquerizo-Villar F, Kheirandish-Gozal L, Gutiérrez-Tobal GC, et al. A convolutional neural network architecture to enhance oximetry ability to diagnose pediatric obstructive sleep apnea. *IEEE J Biomed Health Inform.* 2021;25(8):2906-2916. doi:10.1109/JBHI.2020.3048901.
18. Pang B, Doshi S, Roy B, Lai M, Ehlert L, Aysola R. S, Kang D. W, Anderson A, Joshi S. H, Tward D, Scalzo F, Vacas S, Kumar R. Machine learning approach for obstructive sleep apnea screening using brain diffusion tensor imaging. *J Sleep Res*. 2023;32(1):e13729.
19. Baillieul S, Revol B, Jullian-Desayes I, Joyeux-Faure M, Tamisier R, Pépin JL. Diagnosis and management of central sleep apnea syndrome. Expert Rev Respir Med. 2019;13(6):545-557. doi:10.1080/17476348.2019.1604226
20. Varisco G, Peng Z, Kommers D, Zhan Z, Cottaar W, Andriessen P, Long X, van Pul C. Central apnea detection in premature infants using machine learning. *Comput Methods Programs Biomed*. 2022;226(107155):107155.
21. Ghirardo S, Amaddeo A, Griffon L, Khirani S, Fauroux B. Central apnea and periodic breathing in children with underlying conditions. *J Sleep Res*. 2021;30(6):e13388.
22. Liu J, Chang L, Cao L, Huang G. Distribution characteristics and influencing factors of central apnea in Chinese pediatric patients with obstructive sleep apnea: A single-center study. *Front Pediatr*. 2022;10.
23. Kheirandish-Gozal L, Gozal D, eds. *Sleep Disordered Breathing in Children: A Comprehensive Clinical Guide to Evaluation and Treatment*. Humana Press; 2012.
24. Arlene J, Nundy K, Kumar B, Cardiff J. Somnnet: An spo2 based deep Learning network for sleep apnea detection in smartwatches. In: *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE.
25. Zhu L, Wang C, He Z, Zhang Y. A lightweight automatic sleep staging method for children using single-channel EEG based on edge artificial intelligence. *World Wide Web*. 2022;25(5):1883-1903. doi:10.1007/s11280-021-00983-3
26. Crowson MG, Gipson K. S, Kadosh O. K, Hartnick E, Grealish E, Keamy D. G, Kinane T. B, Hartnick C. J.Paediatric sleep apnea event prediction using nasal air pressure and machine learning. *J Sleep Res*. 2023;32(4):e13851.
27. Kim W. P, Kim H. J, Pack S. P, Lim J. H, Cho C. H, Lee H. J. Machine Learning-Based Prediction of Attention-Deficit/Hyperactivity Disorder and Sleep Problems With Wearable Data in Children. *JAMA Netw Open*. 2023;6(3):e233502.
28. Zhang Z. Federated learning enhanced AR/VR integration in sleep wearable devices. *Appl Comput Eng*. 2024;86:213-220
29. Baron KG, Duffecy J, Berendsen MA, Cheung Mason I, Lattie EG, Manalo NC. Feeling validated yet? A scoping review of the use of consumer-targeted wearable and mobile technology to measure and improve sleep. *Sleep Med Rev*. 2018;40:151-159.
30. Guillodo E, Lemey C, Simonnet M, et al. Clinical applications of mobile health wearable–based sleep monitoring: Systematic review. *JMIR Mhealth Uhealth*. 2020;8(4):e10733.
31. Zhang Z. Federated learning enhanced AR/VR integration in sleep wearable devices. *Appl Comput Eng*. 2024;86:213-220.
32. Katz AL, Macauley RC, Mercurio MR, et al. Informed consent in decision-making in pediatric practice. *Pediatrics*. 2016;138(2):e20161484.
33. Daneshjou R, Smith MP, Sun MD, Rotemberg V, Zou J. Lack of transparency and potential bias in artificial intelligence data sets and algorithms: A scoping review. *JAMA Dermatol*. 2021;157(11):1362-1369.
34. Morley J, Machado CCV, Burr C, et al. The ethics of AI in health care: A mapping review. *Soc Sci Med*. 2020;260:113172.