DOI: 10.7860/JCDR/2026/87848.23984

Review Article

Ear, Nose and Throat Section

Leveraging Artificial Intelligence for the Diagnosis and Management of Obstructive Sleep Apnoea: A Narrative Review

SAURAV RAJNISH SHAH[1], DHWANI SHETH[2], AJAY RAMCHANDRA KAMBLE[3], HARSHIL DOBARIYA[4], VIRAJ GUPTA[5]

ABSTRACT

Recurrent upper airway blockage during sleep, sleep architecture disruption, intermittent hypoxaemia, and increased cardiovascular and neurocognitive morbidity are all symptoms of Obstructive Sleep Apnoea (OSA), a prevalent disease. The gold-standard diagnostic method, Polysomnography (PSG), is limited by patient discomfort, infrastructure requirements, and cost. At the same time, within the frameworks of Machine Learning (ML) and Deep Learning (DL) architectures, Artificial Intelligence (AI) has become a paradigm for change. These can retrieve predictive and diagnostic information from a variety of signals and images. The present review provides an overview of recent AI techniques, including Support Vector Machines (SVM), Random Forests (RF), neural networks, Convolutional Neural Networks (CNN), transformers, and hybrid expert systems, and discusses their applications in OSA screening, event detection, severity estimation, therapy planning, and compliance prediction. Technologies incorporated into wearables or contactless platforms, such as radar sensors, pulse oximeter rings, and AI-enabled household appliances, as well as ENT (Otorhinolaryngology) applications in anatomical phenotyping and surgical outcome prediction, are of particular interest. Thereby, the present review aimed to provide Ear, Nose and Throat (ENT) practitioners with a thorough overview of AI's capabilities, limitations, and potential applications in precision sleep medicine.

Keywords: Machine learning, Polysomnography, Sensors

INTRODUCTION

Approximately one billion people worldwide suffer from OSA. The lack of overnight sleep facilities in laboratories and the technical complexity of PSG, including Electroencephalography (EEG), Electrooculography (EOG), Electromyography (EMG), Electrocardiography (ECG), effort of breathing, airflow, and pulse oximetry sensors, are the main causes of its severe underdiagnoses. It is diagnosed using the Apnoea-Hypopnea Index (AHI) cut-offs: mild (≥5 and <15 events/hour), moderate (≥15 and <30 events/hour), and severe (≥30 events/hour), but at a considerable financial and logistical cost [1]. AI provides an additional diagnostic pathway in otorhinolaryngology (ENT), where treatment decisions are often based on anatomical and functional airway characteristics. In addition to triaging PSG, AI can automate event detection and severity assessment and directly influence individualised treatment decisions [2,3].

Important gaps remain in integrating AI-based diagnostic approaches with ENT-specific anatomical and functional airway assessment. The current review focuses on algorithmic techniques, emerging technology platforms, and their clinical applicability within ENT practice to guide precision-based diagnosis and individualised management of OSA. Hence, the review aimed to assess algorithmic techniques and technology platforms for OSA diagnosis and treatment, compare performance benchmarks with standards, investigate interfacing with wearable, contactless, and ENT-specific modalities, and assess clinical implications for ENT practice and prospects in precision sleep medicine. The novelty of the review lies in integrating AI-based diagnostic and management approaches for OSA with ENT-specific anatomical and functional airway assessment to highlight their potential in enabling precision, individualised sleep medicine.

MATERIALS AND METHODS

Search Strategy

A narrative literature search was conducted using electronic databases, including PubMed, Scopus, Google Scholar, and Web of Science, for studies related to AI and OSA. Relevant articles published between 2017 and 2025 were primarily included based on relevance and scientific contribution. The search terms included 'artificial intelligence', 'machine learning', 'deep learning', 'obstructive sleep apnea', 'polysomnography', and 'wearable devices'.

Inclusion criteria: Studies focusing on AI-based diagnostic, predictive, therapeutic, and wearable-system applications in OSA were included.

Exclusion criteria: Conference abstracts, non-English articles, duplicate publications, and studies lacking adequate methodological detail were excluded.

AI Algorithms and Input Modalities

AI techniques in OSA range from standard ML methods such as SVM, RF, logistic regression, K-Nearest Neighbours (KNN), and Naive Bayes, to newer paradigms like CNN, Transformer models, and hybrid expert systems [4]. Initial efforts with conventional ML models on demographical and anthropometric data achieved high screening specificity. Such traditional models proved superior to conventional questionnaires such as STOP-BANG [3,5]. Modern DL approaches have now handled raw airflow, ECG, and breathing-audio signals end-to-end to achieve approaching 90% sensitivity and specificity in apnoeic event detection and AHI estimation. Sleep PPG Net, a DL model, was trained on raw Photoplethysmography (PPG) signals and achieved robust four-class sleep-stage accuracy, outstanding generalisability to external datasets, and potential wearability and clinical-grade promise [6-8].

Respiratory event detection networks based on CNN architectures effectively discriminate apnoeas, hypopneas, central events, and respiratory effort-related arousals from belt-recorded signals. For example, single-belt WaveNet-based automatic detection achieved 95% accuracy in a database of around 10,000 overnight PSGs and was externally validated. Hybrid rules composed of rule-based expert rules and ML classifiers have been examined for greater interpretability, particularly in ENT use cases where diagnostic transparency is paramount [9,10]. Key studies using AI for the detection or prediction of sleep apnoea events are summarised in [Table/Fig-1] [6,7,9,10]. It includes the type of input data, the model architecture, the task performed, the dataset size, the external validation approach, and the reported performance metrics.

Study	Input data	Model	Task	Dataset size	External validation	AUC/ Accuracy
Setiawan F and Lin CW (2022, Taiwan) [6]	ECG recordings (PhysioNet Apnoea-ECG Database)	1D and 2D CNN with EMD	Detection of sleep apnoea events (normal vs. apnoea)	33 subjects, 7-10 hours ECG per subject	Leave-one-subject-out (LOO) CV	Segment-level: 93.8% accuracy, 94.9% sensitivity, 92.7% specificity; Subject-level: 83.5% accuracy, 75.9% sensitivity, 88.7% specificity
Qin H and Liu G (2022, China) [7]	Single-lead ECG recordings (Apnoea-ECG Database)	1D CNN for representation learning + BiGRU for temporal dependence	Detection of sleep apnoea events (SA vs. normal)	Not specified	Not reported	Per-segment: 91.1% accuracy, 88.9% sensitivity, 92.4% specificity; Per-recording: 100% accuracy
Chen Y et al., (2023, China) [9]	Respiratory vibration signals from piezoelectric sensors	CNN–transformer network	Prediction of sleep apnea events	105 subjects, overnight recordings	LOO CV and five-fold CV	Five-fold CV: 85.9% accuracy, 85.8% F1 score; LOO CV: slightly lower but improved over classical models
Nassi TE et al., (2022, USA) [10]	Polysomnography (PSG) recordings (MGH dataset)	WaveNet neural network	Detection of respiratory events and AHI assessment	9,656 PSG recordings (MGH); external: 8,455 PSG recordings Sleep Heart Health Study-1 (SHHS-1)	External validation on the SHHS-1 dataset	Binary apnea detection: 68% sensitivity, 98% specificity, 65% precision, 67% F1-score, AUC-ROC =0.93, AUC-PR=0.71; Multiclass performance: central apnoea 84%, OSA 51%, hypopnoea 23%, respiratory-effort arousals 40%

[Table/Fig-1]: Summary of AI models for OSA detection and prediction [6,7,9,10].

Abbreviations: ECG: Electrocardiography; CNN: Convolutional neural network; EMD: Empirical mode decomposition; CV: Cross-validation; BiGRU: Bidirectional gated recurrent unit; PSG: Polysomnography; AUC: Area under the curve; ROC: Receiver operating characteristic; PR: Precision-recall

Contactless and Wearable Systems

Wearable sensors, such as rings, patches, chest straps, and wristbands, paired with AI software, are one potential way to conduct long-term, home-based OSA monitoring. Devices such as watches, patches, or rings utilise CNN-based and transfer-learning models with high event-detection accuracy. Contactless devices employ millimetre-wave radar in conjunction with pulse oximetry, employing deep neural networks for event detection and sleep stage identification [11].

Ring-style, FDA-cleared devices have demonstrated good patient compliance in preliminary studies, which is more valuable to some physicians than single-night, full-channel PSG. However, these approaches vary in accuracy, with wearable sensors generally performing well for long-term trend monitoring but less precise for single-event detection compared to PSG; contactless devices may face challenges with signal noise, body movement, and consistent alignment with clinical standards Non contact and wearable strategies reduce patient burden, lower technical intricacy, and offer scalable diagnosis pathways suitable for ENT clinics, primary care, or population-level screening [12].

AI in Therapeutic Planning and ENT-specific Applications

Surgeries for OSA- Uvulopalatopharyngoplasty (UPPP), Hypoglossal Nerve Stimulation (HNS), and Trans Oral Robotic Surgery (TORS)- have previously had variable success rates. Demographic, PSG, Drug-Induced Sleep Endoscopy (DISE), and Friedman staging data used to train gradient boosting and logistic regression models accurately predicted postoperative outcomes, outperforming surgeon estimation alone- the gradient boosting model was accurate for subjective estimation. Linking phenotyping to AI approaches, gradient boosting, and logistic regression have been particularly effective for predicting surgical outcomes, while unsupervised clustering identifies patient subgroups that may benefit from targeted interventions [3,13].

Stimulation of the HNS for improved tongue protrusion with implanted electrodes has some eligibility criteria: Body Mass Index (BMI) values, lack of concentric palatal collapse, and primarily obstructive AHI. ML methods that recognise NED patterns in diagnostic PSG can forecast HNS responders, with low NED breath rates associated with successful therapy. Supervised ML models applied to PSG-derived NED patterns provide the best predictive performance for HNS response, illustrating how specific AI techniques can guide treatment selection [2,4,14].

Unsupervised classification of clinical and physiological variables has identified OSA phenotypes- e.g., patients defined by neural arousal sensitivity prevalence, low symptom load but high comorbidity load, or severe sleepiness- that may require tailored treatment approaches, behavioural, device-based, or anatomical. Predicting Continuous Positive Airway Pressure (CPAP) therapy adherence using trained ML models derived from early use history and baseline physiology enables timely intervention. Models capable of identifying patients who are likely to struggle can initiate behavioural treatment, telehealth coaching, or other interventions, thereby increasing long-term compliance. Integrating these phenotypes with appropriate AI models enables selection of optimal predictive methods for each patient subgroup, linking phenotype discovery with actionable AI-driven treatment planning [15-17].

In real-world ENT clinical practice, ML models enable surgical decision-making by integrating imaging, endoscopic video, and PSG-derived inputs to predict response to UPPP, TORS, or HNS- preventing unnecessary surgery and enabling planning interventions based on patient phenotype [13,15].

AI as PSG Alternative in Low-resource Settings

The AI offers a promising alternative to PSG in low-resource settings where access to specialised sleep labs is limited. By leveraging wearable devices, single-lead ECG, or contactless monitoring systems, AI models can automatically detect and classify OSA events with high accuracy, reducing the need for overnight, full-channel PSG. Such approaches enable decentralised sleep assessment, reducing costs and patient burden while providing scalable solutions for regions without dedicated sleep clinics. In primary care and telemedicine contexts, AI-driven OSA screening can facilitate early identification of at-risk individuals. Remote monitoring using AI-enabled wearable sensors or contactless devices allows continuous data collection and automated analysis, enabling sleep specialists to prioritise high-risk patients and provide timely interventions. Integration with telemedicine platforms can support virtual sleep labs, where patients are guided remotely, and AI algorithms analyse data in real time, enhancing accessibility and efficiency while maintaining clinical decision-making standards [3,11,12].

Clinical Integration and Workflow Considerations

AI application in ENT settings must be deliberately integrated to achieve clinical advantage. Anthropomorphic or questionnaire-based models can perform patient triage in a practical, non invasive way, triage pathway before PSG. Including AI models in endoscopic or imaging data streams permits real-time assessment of multilevel airway collapse. It may even be able to supply input to ENT surgeons regarding levels of intervention [18]. Integrating decision-support modules and Electronic Health Records (EHR) can facilitate risk-standardised measurement and flag high-risk patients. Clinician uptake is subject to transparency: explainable AI methods or rule-based reasoning engender trust over solely black-box DL models [16,19].

Experts in ENT and rhinology report cautiously optimistically that they most welcome AI as an add-on, not a replacement, for clinician judgment. From a regulatory and medicolegal perspective, AI deployment requires adherence to medical device approvals, data protection laws, and clinical governance frameworks. Implementation studies, workflow integration, costs, and training requirements need to be considered. Generalisability is a concern, as all models have been developed from homogeneous datasets; cross-group validation and testing across multiple clinical settings are needed to ensure applicability beyond initial cohorts. In Outpatient Department (OPD) screening pathways, AI tools can assist clinicians by flagging high-risk patients early, streamlining triage, and prioritising diagnostic tests, complementing current standard care. Ethical considerations of data privacy, sampling bias, consent, and explainability are essential for safe and legally compliant clinical adoption [18,20,21].

AI in OSA management has significant clinical implications beyond technological innovation. It can support early screening in primary care or ENT clinics by identifying high-risk patients, reducing dependence on overnight PSG, and enabling timely referrals. AI-assisted analysis of endoscopic, imaging, and PSG-derived data can guide surgical planning, predict therapy response, and personalise treatment pathways for interventions such as CPAP, HNS, or UPPP. Remote monitoring using wearable or contactless devices allows continuous assessment of therapy adherence, symptom progression, and disease severity, providing clinicians with actionable insights for individualised care. By integrating AI outputs into clinical workflows and decision-support systems, practitioners can make evidence-based decisions more efficiently, improve patient counselling, and optimise resource allocation, ultimately enhancing both patient outcomes and operational efficiency in sleep medicine practice [3,4,20].

Future Directions

New OSA frontiers for AI include explainable ML models that can be audited by physicians, multimodal fusion of wearables, speech analysis, imaging, and questionnaire data, integrated into synthesis pipelines deployable in primary care or telemedicine. Applying transformer architectures to temporal event detection promises early potential [11,22]. In ENT, using three-dimensional airway modelling, video examination of DISE, and AI-based prediction of obstruction location can aid surgical planning during live surgery or intraoperative guidance, thereby enabling more accurate intervention. Adaptive real-time treatments, such as auto-titrating CPAP with AI-driven steering or closed-loop HNS devices, represent a future therapeutic approach for automatic therapy adjustment based on physiologic signals [2,23]. Regulatory innovation and reimbursement models will pave the way to clinical scale. Multidisciplinary partnerships with clinicians, engineers, regulators, and payers will be required. Transparency of algorithms during the development phase, prospective clinician validation studies, and clinician education programs will also enable large-scale adoption [3,4].

Limitation(s)

Despite its promising potential, integrating AI into OSA diagnosis and treatment faces several limitations. First, many AI models are trained on homogeneous datasets, raising concerns about their generalisability across diverse patient populations and clinical settings. Additionally, the clinical adoption of AI tools is contingent on their integration with existing workflows, which may require significant infrastructure changes, staff training, and cost considerations. Moreover, AI models, particularly DL systems, often operate as "black boxes," making it difficult for clinicians to interpret their decision-making processes. This lack of transparency may hinder trust and uptake in clinical practice. Ethical concerns regarding data privacy, informed consent, and potential biases in algorithmic predictions must also be addressed to ensure the safe and equitable use of AI. Finally, regulatory approvals and medicolegal considerations must be thoroughly navigated before AI tools can be fully integrated into routine clinical practice [3,4,23].

CONCLUSION(S)

The AI, encompassing ML and DL techniques, has the potential to improve OSA management by yielding greater speed, precision, accessibility, and personalisation of diagnosis and treatment. Contactless and wearable technologies enable scalable, long-term monitoring; algorithms enable surgical candidacy assessment, CPAP compliance prediction, and phenotype-guided treatment planning. Clinicians in ENT can gain a lot from anatomical insights and decision support enabled by AI analysis. Despite issues with validation, explainability, and clinical uptake, the growing maturity of AI tools means they will be able to complement clinical practice. With continuous research, multicentre validation, explainability enhancement, and clinician engagement, AI has the potential to significantly support precision sleep medicine in otorhinolaryngology.

REFERENCES

[1] Abbasi A, Gupta SS, Sabharwal N, Meghrajani V, Sharma S, Kamholz S, et al. A comprehensive review of obstructive sleep apnea. Sleep Sci Sao Paulo Braz. 2021;14(2):142-54.

[2] Demir E, Uğurlu BN, Uğurlu GA, Aydoğdu G. Artificial intelligence in otorhinolaryngology: Current trends and application areas. Eur Arch Otorhinolaryngol. 2025;282(5):2697-707.

[3] Bhatt SP, Khurana A. Artificial intelligence in obstructive sleep apnea: Transforming diagnosis and management. Respir Med. 2025;243:108100.

[4] Bazoukis G, Bollepalli SC, Chung CT, Li X, Tse G, Bartley BL, et al. Application of artificial intelligence in the diagnosis of sleep apnea. J Clin Sleep Med. 2023;19(7):1337-63.

[5] Behar JA, Palmius N, Li Q, Garbuio S, Rizzatti FPG, Bittencourt L, et al. Feasibility of single channel oximetry for mass screening of obstructive sleep apnea. EClinicalMedicine. 2019;11:81-88.

[6] Setiawan F, Lin CW. A deep learning framework for automatic sleep apnea classification based on empirical mode decomposition derived from single-lead electrocardiogram. Life. 2022;12(10):1509.

[7] Qin H, Liu G. A dual-model deep learning method for sleep apnea detection based on representation learning and temporal dependence. Neurocomputing. 2022;473:24-36.

[8] Raisa RA, Rodela AS, Yousuf MA, Azad A, Alyami SA, Liò P. Deep and shallow learning model-based sleep apnea diagnosis systems: A comprehensive study. IEEE Access. 2024;12:122959-87.

[9] Chen Y, Yang S, Li H, Wang L, Wang B. Prediction of sleep apnea events using a CNN–transformer network and contactless breathing vibration signals. Bioengineering. 2023;10(7):746.

[10] Nassi TE, Ganglberger W, Sun H, Bucklin AA, Biswal S, van Putten MJAM, et al. Automated scoring of respiratory events in sleep with a single effort belt and deep neural networks. IEEE Trans Biomed Eng. 2022;69(6):2094-104.

[11] Bhalsod D, Taksande K, Paul A, Patel V. Bridging the gap between ICU and home-based care: A review of wearable technologies and remote monitoring in critical care. Multidiscip Rev. 2025;8(8):2025256.

[12] Vitazkova D, Kosnacova H, Turonova D, Foltan E, Jagelka M, Berki M, et al. Transforming sleep monitoring: Review of wearable and remote devices advancing home polysomnography and their role in predicting neurological disorders. Biosensors. 2025;15(2):117.

[13] Spyropoulou A, Spiropoulos V, Spiropoulou G, Tsilivigos C, Spiropoulos K, Mastronikolis N. Surgical approaches in obstructive sleep apnea syndrome: A review of techniques. Pneumon. 2022;35(3):01-10.

[14] Baptista PM, Costantino A, Moffa A, Rinaldi V, Casale M. Hypoglossal nerve stimulation in the treatment of obstructive sleep apnea: Patient selection and new perspectives. Nat Sci Sleep. 2020;12:151-59.

[15] Zinchuk AV, Gentry MJ, Concato J, Yaggi HK. Phenotypes in obstructive sleep apnea: A definition, examples and evolution of approaches. Sleep Med Rev. 2017;35:113-23.

[16] Abu K, Khraiche ML, Amatoury J. Obstructive sleep apnea diagnosis and beyond using portable monitors. Sleep Med. 2024;113:260-74.

[17] Ghorvei M, Karhu T, Hietakoste S, Ferreira-Santos D, Hrubos-Strøm H, Islind AS, et al. A comparative analysis of unsupervised machine-learning methods in PSG-related phenotyping. J Sleep Res. 2025;34(3):e14349.

[18] Dallari V, Liberale C, De Cecco F, Nocini R, Arietti V, Monzani D, et al. The role of artificial intelligence in training ENT residents: A survey on ChatGPT, a new method of investigation. Acta Otorhinolaryngol Ital. 2024;44(3):161-68.

[19] Dinh-Le C, Chuang R, Chokshi S, Mann D. Wearable health technology and electronic health record integration: Scoping review and future directions. JMIR MHealth UHealth. 2019;7(9):e12861.

[20] Tama BA, Kim DH, Kim G, Kim SW, Lee S. Recent advances in the application of artificial intelligence in otorhinolaryngology-head and neck surgery. Clin Exp Otorhinolaryngol. 2020;13(4):326-39.

[21] Alshehri S, Alahmari KA, Alasiry A. A comprehensive evaluation of AI-assisted diagnostic tools in ENT medicine: Insights and perspectives from healthcare professionals. J Pers Med. 2024;14(4):354.

[22] Huang G, Chen X, Liao C. AI-driven wearable bioelectronics in digital healthcare. Biosensors. 2025;15(7):410.

[23] An X, Zhou J, Xu Q, Zhao Z, Li W. Artificial intelligence in obstructive sleep apnea: A bibliometric analysis. Digit Health. 2025;11:20552076251324446.

PARTICULARS OF CONTRIBUTORS:

1. Junior Resident, Department of Otorhinolaryngology, Jawaharlal Nehru Medical College, Datta Meghe Institute of Higher Education and Research, Wardha, Maharashtra, India.
2. Junior Resident, Department of Anaesthesiology, Jawaharlal Nehru Medical College, Datta Meghe Institute of Higher Education and Research, Wardha, Maharashtra, India.
3. Professor, Department of Otorhinolaryngology, Jawaharlal Nehru Medical College, Datta Meghe Institute of Higher Education and Research, Wardha, Maharashtra, India.
4. Senior Resident, Department of Otorhinolaryngology, Jawaharlal Nehru Medical College, Datta Meghe Institute of Higher Education and Research, Wardha, Maharashtra, India.
5. Junior Resident, Department of Radiodiagnosis, Jawaharlal Nehru Medical College, Datta Meghe Institute of Higher Education and Research, Wardha, Maharashtra, India.

NAME, ADDRESS, E-MAIL ID OF THE CORRESPONDING AUTHOR:
Dr. Saurav Rajnish Shah,
Junior Resident, Department of Otorhinolaryngology, Jawaharlal Nehru Medical College, Sawangi (Meghe), Wardha-442001, Maharashtra, India.
E-mail: sauravshah731@gmail.com

PLAGIARISM CHECKING METHODS: [Jain H et al.]

- Plagiarism X-checker: Feb 22, 2026
- Manual Googling: Apr 27, 2026
- iThenticate Software: Apr 29, 2026 (1%)

ETYMOLOGY: Author Origin

EMENDATIONS: 5

AUTHOR DECLARATION:

- Financial or Other Competing Interests: None
- Was informed consent obtained from the subjects involved in the study? NA
- For any images presented appropriate consent has been obtained from the subjects. NA

Date of Submission: **Jan 30, 2026**
Date of Peer Review: **Mar 05, 2026**
Date of Acceptance: **May 01, 2026**
Date of Publishing: **Aug 01, 2026**