

## Letter to Editor

### Advancing Outpatient Diagnosis of Obstructive Sleep Apnoea through Artificial Intelligence: Promise and Pitfalls

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Obstructive Sleep Apnoea (OSA) is a prevalent and clinically significant disorder of sleep characterized by recurrent episodes of sleep-related airflow obstruction despite continued respiratory effort. These events are predominantly caused by obstruction of the upper airway. These events are frequently accompanied by daytime somnolence, sleep disturbance, and recurrent hypoxia. A meta-analysis of 17 studies approximates that about 425 million people worldwide (95% CI: 399–450 million) have moderate-to-severe OSA aged 30 to 69 years.<sup>1</sup> OSA is among the most underdiagnosed and undertreated of noncommunicable diseases worldwide, reflecting its high burden.

The pathophysiologic consequences of OSA extend far beyond mere disturbance of sleep. Multiple studies have found robust links between OSA and systemic hypertension, coronary heart disease, stroke, atrial fibrillation, type 2 diabetes mellitus, cognitive impairment, and even oncogenic potential.<sup>2</sup> Therefore, early diagnosis and management are required to avoid long-term neurological, metabolic, and cardiovascular morbidity and improve quality of life.

Polysomnography has many advantages but with pros comes the cons like expenses, time taking methods, need for high maintenance instruments and

skilled officials. These setbacks have pivoted the way of interest in direction of time saving, more easily approachable and measurable screening opportunities that are favorable to working environment and accelerate the best outcome with limited resources. With Artificial Intelligence being the owner of modern technology, procedures like advanced and deep Machine Learning have become core of diagnostics in recent developments, supported by proof in scanning for obstructive sleep apnea (OSA), in which AI-controlled systems are being constructed to overtake the manual interpretations for electrocardiography (ECG) and oxygen saturations (SpO<sub>2</sub>) in running time, minimizing the need for laboratory services.

An appreciable approach in this field of AI is Type IV Artificial Intelligence Sleep Monitoring (AISM) device. With minimum expenditure, this detects OSA biomarkers with barely any invasion and costs are lowered down. These developments have impacted in neglecting unnecessary lab tests that are costly, prioritizing the patient comfort and short listing for PSG,<sup>3</sup> and efficient to detect early triage equity. Based on these advantages, AI screening tools are being designated as significant for early diagnosis of OSA.

Simple clinical characteristics like age, sex, and body mass index (BMI) are used in AI-based predictive models, which have shown great success. Both logistic regression (LR) and artificial neural network (ANN) models obtained area under the curve (AUC) values of 0.806 and 0.807, respectively, in identifying moderate-to-severe obstructive sleep apnea (OSA)



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with an apnea-hypopnea index (AHI) of 15 or higher, according to a large-scale study that involved 9,422 adults who underwent polysomnography (PSG). These models' promise for pre-screening was confirmed by their excellent sensitivity (above 87%) and significant positive predictive value (above 77%). These findings unequivocally demonstrate that, with the right training and validation, even basic models can perform diagnostically on par with more sophisticated systems. In many clinical contexts, interpretable algorithms such as logistic regression are adequate for first-line screening, as demonstrated by the same accuracy of the ANN and LR models.<sup>4</sup>

The inherent advantages of artificial intelligence-based screening tools make them paradigmatic for the early diagnosis of obstructive sleep apnea (OSA). Their cost-effectiveness enables mass screening programs, and they can be used both in outpatient and home settings without the requirement of advanced diagnostic equipment such as polysomnography. Their accessibility makes them particularly valuable in low-resource environments that lack specialized healthcare facilities. Moreover, a number of these techniques provide real-time feedback, thereby enabling timely clinical decision-making. These advantages emphasize the capability of AI to bridge diagnostic gaps and enhance patient outcomes across various healthcare settings.

Yet, considering these advantages, it is essential that artificial intelligence models undergo stringent validation using well-standardized instruments like polygraphy (PG), Home Sleep Apnea Testing (HSAT), and screening instruments like STOP-Bang and NoSAS scores.<sup>5</sup> They were prevalent measures that have been found to perform well clinically in the overall population regardless of their ability to provide physiological measurements in fine detail.

Cost-benefit analysis is needed for artificial intelligence deployment in clinical practice. Accounting for threshold probabilities as well as for the effects of false positives and false negatives, methods like Decision Curve Analysis (DCA) provide a quantitative means of assessing net therapeutic benefits. Unlike conventional logistic regression-based methods, DCA has demonstrated that AI models can improve diagnostic accuracy.<sup>6</sup> Notably, AI pre-screening-facilitated targeted referral can reduce unnecessary polysomnographies (PSGs) and better allocate resources to high-risk individuals. The future of AI-driven OSA diagnosis,

while promising results, is subject to hybrid systems that merge clinical knowledge with computational power through AI integration with decreased physiological data. Enhanced performance can be achieved by incorporating patient-reported measures, combining Electronic Health Records (EHRs), and personalizing the model via federated learning. Furthermore, studies continue in domains of explainability, ethical clearance, and regulatory endorsement. The "black-box problem" the challenge of knowing and trusting AI-driven decisions necessitates explainable model interpretability and bias prevention techniques.

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