Review Article

Artificial intelligence in screening for obstructive sleep apnoea syndrome (OSAS): a narrative review

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Background and Objective: Obstructive sleep apnoea syndrome (OSAS) is an increasingly common disorder, characterized by repeated upper airway collapse during sleep, resulting in oxygen desaturation and disrupted sleep. Untreated OSAS leads to a range of downstream diseases and patients with OSAS bring great challenges to anesthesia management as well. Considering that the recognized gold standard for the diagnosis of OSAS, the full-night, in-laboratory polysomnography (PSG) is expensive, and accessibility to a sleep facility is not always easy, some quick, convenient, and intelligent screening tools are necessary. Artificial intelligence (AI) has grown considerably in the prediction of OSAS over the past few years. This review summarizes current AI techniques used for screening strategies applied to OSAS.

Methods: PubMed, Cochrane, Scopus, and Web of Science databases were searched with related keywords. All publication types in English between January 1993 and July 2022 were included.

Key Content and Findings: AI has been extensively studied in screening for OSAS. AI can help develop an accurate screening model based on the patients' anthropometric data or combined with some simple physiological signals. Patients with OSAS always have craniofacial structure and upper airway abnormalities. Therefore, it is possible to develop an automatic system for the screen for OSAS by their facial images and 3D scans based on the AI algorithm. Finally, non-invasive wearable devices are becoming ubiquitous and provide new opportunities to predict OSAS. By measuring the electrocardiograph (ECG), oxygen saturation (SaO_2), heart rate, or breathing sound, patients with OSAS can be screened.

Conclusions: AI has the potential to screen patients on a large scale who may have OSAS for subsequent PSG to reduce the medical burden and reduce OSAS-related complications for patients.

Keywords: Obstructive sleep apnoea syndrome (OSAS); artificial intelligence (AI); screen

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Introduction

Obstructive sleep apnoea syndrome (OSAS) is an increasingly common disorder, characterized by repeated upper airway collapse during sleep, resulting in oxygen desaturation and disrupted sleep (1). Patients with OSAS show snoring, witnessed apnoeas, waking up with a choking sensation, and excessive sleepiness. Non-restorative sleep, difficulty initiating or maintaining sleep, fatigue or tiredness, and morning headache are common in patients with OSAS (1).

The collapse of the upper airway results in intermittent hypoxia, intrathoracic pressure swings, sympathetic surges, and sleep fragmentation. Therefore, OSAS is related to a range of diseases including hypertension (2), coronary heart

disease and heart failure (3), cerebrovascular disease (4), cognitive deficit (5), and metabolic syndrome (6). Early diagnosis of OSAS is essential.

The apnoea-hypopnea index (AHI) is used to describe the number of apnoeas and hypopneas per hour of sleep. OSAS is defined as an AHI of 5 or more events per hour. The severity of OSAS can also be categorized by AHI. Patients with an AHI of 5–15 events/h, 16–30 events/h, or more than 30 events/h are considered to have mild, moderate, or severe OSAS, respectively. OSAS has become a huge burden on medical care, and the number of patients is still on the rise. A recent systematic review reported that the overall population prevalence ranged from 9% to 38% at ≥5 events/h AHI while at 15 events/h AHI, the prevalence in the general adult population ranged from 6% to 17% (7). The prevalence appears to be increasing. A study from the United Kingdom demonstrated a significant increase in the rates of OSAS over the last 20 years (8).

With an increasing prevalence of OSAS and an overall growth in the number of surgical procedures, patients with potential OSAS presenting for surgery will grow substantially. OSAS brings great challenges to anesthesia management, especially unanticipated OSAS. OSAS is an independent risk factor for difficult intubation and mask ventilation, which is related to most severe anesthesia-related complications including death or hypoxic brain injury (9). A meta-analysis including 13 studies confirmed that patients with OSAS may have a higher incidence of postoperative complications. OSAS was associated with increased incidence of desaturation, respiratory failure, cardiac events, and intensive care unit admission as well (10). The severity of obstructive sleep apnoea (OSA) defined by AHI has not been shown to correlate with risk for postoperative complications (11,12). The Society of Anesthesia and Sleep Medicine (SASM) Guidelines on Preoperative Screening and Assessment of Adult Patients With Obstructive Sleep Apnoea emphasized that adult patients at risk for OSA should be identified before surgery (13). Patients with OSAS required a specific protocol including anesthesia methods, choice of medications, monitoring, and appropriate preoperative or postoperative strategy to reduce complications.

The gold standard for diagnosing OSAS is in-laboratory polysomnography (PSG) to measure the frequency of obstructed breathing events during sleep. There is a significant cost to evaluate all suspected patients with PSG because medical personnel are required for continuous sleep monitoring. Furthermore, in-lab testing is not always easy to get in some areas (14). Unattended portable monitoring (PM) can be an alternative to PSG. However, PM is not appropriate for the diagnosis of OSA in patients with significant comorbid medical conditions and patients suspected of having comorbid sleep disorders. In addition, PM is not appropriate for the general screening of asymptomatic populations (15). As a result, it is necessary to explore simple approaches for screening OSAS in a massive population to achieve early diagnosis and early treatment to reduce potential harm and complications. The SASM guidelines also recommended screening for surgical patients with suspected OSAS in the preoperative period (13). There are many different screening approaches including questionnaires and clinical models, but there is a large heterogeneity within each screening tool (16). If appropriately used, AI may streamline clinical operations, and introduce greater precision into the screening for OSAS.

Artificial intelligence (AI) refers to the ability of computer systems to perform tasks historically executed only by humans. Recent AI research has leveraged machine learning (ML) methods. ML is described as 'giving computers the ability to learn without being explicitly programmed'. ML can be supervised, unsupervised, or reinforcement learning. Most studies on OSAS screening rely on supervised learning. In supervised learning, the computer is provided a labeled dataset as input such as patient demographics, and a hypothesis as output that best fits the labeled dataset such as diagnoses to identify links between those two in the dataset (17).

The development of AI in medicine has grown rapidly in the last few decades, especially in sleep medicine. They provide a wide range of techniques, from neural networks that can analyse imaging to sophisticated predictive models. The PSG includes massive physiological data such as electroencephalography (EEG), electro-oculography (EOG), electromyogram (EMG), electrocardiograph (ECG), and recordings of airflow, respiratory effort, oxygen saturation (SaO_2) (18), which is particularly suitable for analysis using AI techniques. AI methods offer the opportunity to assist sleep staging as well as scoring associated events automatically to enhance sleep laboratory efficiency (19).

AI has also been introduced to screen for OSAS and holds great promise to optimize the OSAS diagnosis and treatment process. This review will focus specifically on AI used in the screening for OSAS. Based on the anthropometric characteristics and some simple physiological signals, the prediction model can be proposed for objective screening for OSAS. Patients with OSAS

Table 1 The search strategy summary

Items	Specification
Date of search	2022.8.1
Databases and other sources searched	PubMed, Cochrane, Scopus and Web of Science
Search terms used	See *Table 2*
Timeframe	1993.1–2022.7
Inclusion and exclusion criteria	Inclusion: English article
Selection process	Relevant information was extracted by two reviewers independently

Table 2 Detailed search strategy

Search strategy	Database
Systematic search: Keywords: ("Obstructive Sleep Apnoea Syndrome" OR "OSAS" OR "OSA") AND ("Artificial intelligence" OR "AI") AND ("screen" OR "prediction"); ("Obstructive Sleep Apnoea Syndrome" OR "OSAS" OR "OSA") AND ("deep learning" OR "machine learning") AND ("screen" OR "prediction"); ("Obstructive Sleep Apnoea Syndrome" OR "OSAS" OR "OSA") AND "intelligent devices" AND ("screen" OR "prediction"); ("Obstructive Sleep Apnoea Syndrome" OR "OSAS" OR "OSA") AND "intelligent devices" AND ("screen" OR "prediction"); ("Obstructive Sleep Apnoea Syndrome" OR "OSAS" OR "OSA") AND "wearable devices" AND ("screen" OR "prediction")	PubMed, Cochrane, Scopus, and Web of Science

OSAS, obstructive sleep apnoea syndrome; AI, artificial intelligence; OSA, obstructive sleep apnoea.

always have an anatomic abnormality, which can be screened out by patients' facial images and 3D scanning. ML can analyze data collected by ubiquitous wearable devices so they may hold promise to be a convenient and inexpensive adjunct to clinical evaluation. We present the following article in accordance with the Narrative Review reporting checklist (available at https://jmai.amegroups.com/article/view/10.21037/jmai-22-79/rc).

Methods

A literature search was performed using the PubMed, Cochrane, Scopus and Web of Science databases between January 1993 and July 2022. The search strategy was shown in *Table 1*. The following keywords were used in the search: ("Obstructive Sleep Apnoea Syndrome" OR "OSAS" OR "OSA") AND ("Artificial intelligence" OR "AI") AND ("screen" OR "prediction"); ("Obstructive Sleep Apnoea Syndrome" OR "OSAS" OR "OSA") AND ("deep learning" OR "machine learning") AND ("screen" OR "prediction"); ("Obstructive Sleep Apnoea Syndrome" OR "OSAS" OR "OSA") AND "intelligent devices" AND ("screen" OR "prediction"); ("Obstructive Sleep Apnoea Syndrome" OR "OSAS" OR "OSA") AND "intelligent devices" AND ("screen" OR "prediction"); ("Obstructive Sleep Apnoea Syndrome" OR "OSAS" OR "OSA") AND "wearable devices" AND ("screen" OR "prediction"). The detailed search strategy was shown in *Table 2*. All publication types in English were included. The titles and abstracts of all literatures were screened for relevance. Relevant information was extracted by two reviewers independently.

Content and findings

Screening model based on the clinical features

Numerous studies were devoted to exploring whether AI could offer the opportunity to analyse sleep-associated events automatically and extract additional insights from PSG data. Although fully automated analysis of PSG will be possible in the near future, it doesn't seem to be easy to prescribe PSG for all suspected patients. Selecting the appropriate patients for PSG was determined by evaluating the risk factors of patients. This process used to be subjective, whether AI could offer the opportunity to make this decision more objective and accurate by data mining.

Obesity (especially with body mass index >35 kg/m^2) is a major risk factor for OSAS, and the risk for OSA increases with obesity increasing (20). In addition, men appear to

be more likely to suffer from OSAS than women (21). Other risk factors include waist circumference, waist-to-height ratio (22), family history, and retrognathia (20). Determining the significant predictors of OSAS severity such as body mass index (BMI) and sex to establish a prediction model by ML approaches may help screen for OSAS. Examples of the screening models described later are outlined in *Table 3*.

Two decades ago, scholars from Canada proposed that using 23 clinical variables to train the prediction model based on the generalized regression neural network (GRNN) could accurately classify patients with OSAS (23). The accuracy of the trained GRNN was up to 91.3%. A large retrospective study in 10,391 patients used only five easily available clinical features (age, sex, BMI, neck circumference, and waist circumference) to develop the age and sex independent model by various ML methods including logistic regression (LR), k-nearest neighbor (KNN), naive Bayes (NB), random forest (RF), and support vector machine (SVM) (24). All models exhibited superior performance, among which, RF models showed best with an area under the curve (AUC) between 88.73–97.88% in both mild-moderate OSAS and moderate-severe OSAS which was defined as AHI ≥15 events/h and AHI ≥30 events/h, respectively (24). A previous study proposed a data mining-driven SVM model with only 2 features (waist circumference and age) with an AUC of 82% when AHI cutoff ≥5 events/h (25). When AHI cutoff ≥15 and ≥30 events/h, the proposed model included features of minutes of sleep onset latency (SOL) <30 min which is rare in other researches. Despite the high accuracy, clinicians should be cautious about the results, as the models were not prospectively verified in other populations. In addition, the clinical features included in the model were body variables rather than craniofacial factors, and the latter were associated with OSAS closely.

Given that the clinical variables included in the prediction model are simple and readily available without specific medical instruments, the proposed model after prospective validation can be embedded in the mobile app for screening in large populations (29).

Several studies have combined some physiological signals such as ECG, blood pressure (BP), and blood oxygen monitoring with clinical features to train the model. Theoretically, the combined model should have better performance for screening, but the reality is not always satisfactory.

Papini and colleagues presented using ECG-based features (heart rate variability features and ECG-derived activity counts) with their algorithm to detect OSA-related events and screening OSAS severities with an AUC ≥0.86, Cohen's kappa ≥0.53 (26). A study obtained three readily available features including waist circumference, mean BP at the end of PSG, and the difference in systolic BP between the end and start of PSG by stepwise regression analysis to train the explainable fuzzy neural network (EFNN). The proposed model showed unsatisfactory performance for OSAHS diagnosis at an AHI ≥5 events/h while for patients' moderate-to-severe OSAS, the EFNN model could be a competitive prediction tool (27). Behar and colleagues combined SaO_2 signals during sleep periods and demographic information to train an LR classifier and achieved an AUC of 0.94 (28).

The risk factors such as BMI, age, sex, and waist circumference are good predictors for OSAS and were widely used in prediction models based on a ML algorithm. The different algorithm has been trained but none of them appeared to be superior to the other, which may be related to different populations and different dataset used. In some studies, the combined use of physiological signals and anthropometric characteristic did not show better performance than anthropometric data alone which may result from the inappropriate physiological signals used. It seems that SaO_2 signals are better predictors than ECG or BP. Future studies can focus on what kind of combination can achieve the best prediction ability.

Facial images and 3D scans

Craniofacial structure and upper airway abnormalities, such as skeletal abnormalities or enlarged upper airway soft tissues increase the likelihood of OSAS by compromising pharyngeal airway space (30). Obesity is also a widely recognized risk factor for OSAS (31). AI can help screen for OSAS by detecting these abnormalities through patients' facial images. Facial images can provide not only a composite measure of craniofacial skeletal and soft tissue risk factors (obesity) but also information about underlying skeletal and upper airway soft structure (32). Facial recognition for the prediction of OSAS is non-invasive, convenient, and intelligent, worth studying, and has a great prospect. A summary of the characteristics of the relevant studies is outlined in *Table 4*. ML is widely used, which refers to the study and development of systems that can learn from and make predictions without the need to be programmed (38).

Lee and colleagues (33) developed clinical prediction

Table 3 Examples of screening models based on clinical features and some physiological signals

Author/year	Design	Population number and information	Characteristics	Source of data	Reference standard	Methods	Performance			
							AUC	Se (%)	Sp (%)	Other
Kirby SD/1999, (23)	R	405, clinical	Age, sex, frequent awakening, observed choking, reported excessive daytime sleepiness, Epworth sleepiness scale, hypertension, alcohol, smoke, height, weight, BMI, systolic BP, tonsillar enlargement, soft palate enlargement, crowding of the oral pharynx, clinical score	EHR	AHI >10 events/h	GRNN	0.94	98.9	80	ACC: 91.3%
Tsai CY/2022, (24)	R	10,391, clinical	Age, sex, BMI, NC, WC	Observational data	AHI ≥15 events/h	LR, KNN, NB, RF, SVM	0.89–0.98	NA	NA	ACC: 84.59%±2.35% (RF)
					AHI ≥30 events/h		0.92–0.97	NA	NA	ACC: 81.50%±2.32% (RF)
Huang WC/2020, (25)	R	7,830, clinical	WC, age	EHR	AHI ≥5 events/h	SVM	0.82	74.14	74.71	
			WC, age, NC, snoring, witnessed apnoea, SOL <30 min		AHI ≥15 events/h		0.80	75.18	68.7	
					AHI ≥30 events/h		0.78	70.26	70.30	
Papini GB/2019, (26)	R	262 recordings in 5 datasets, clinical	ECG	EHR	AHI ≥5 events/h	RE-epoch	0.86	85	73	ACC: 84%
					AHI ≥10 events/h		0.86	73	81	ACC: 72%
					AHI >15 events/h		0.90	70	90	ACC: 70%
Juang CF/2021, (27)	R	300, clinical	WC; mean BP at the end of PSG, the difference in SBP between the end and start of PSG	Research data	AHI ≥5 events/h	EFNN	NA	98.2	5.3	ACC: 75%
					AHI ≥15 events/h		NA	79.3	64.7	ACC: 72%
					AHI ≥30 events/h		NA	57.3	87.6	ACC: 80%
Behar JA/2019, (28)	R	887, community	ODI, $MSpO_2$, SpO_2 Nadir, T90	EHR	AHI ≥5 events/h	LR	0.94	87	85	ACC: 86%

AUC, area under the receiver operating characteristics curve; Se, sensitivity; Sp, specificity; R, retrospective; BMI, body mass index; BP, blood pressure; NC, neck circumference; WC, waist circumference; SOL, minutes of sleep onset latency; ECG, electrocardiograph; PSG, polysomnography; SBP, systolic blood pressure; ODI, the 3% oxygen desaturation index; $MspO_2$, the mean oxygen saturation; SpO_2 Nadir, lowest value of oxygen saturation; T90, the proportion of time spent with oxygen saturation under 90%; EHR, electronic health record; AHI, apnoea-hypopnea index; GRNN, generalized regression neural network; LR, logistic regression; KNN, k-nearest neighbor; NB, naive Bayes; RF, random forest; SVM, support vector machine; RE, respiratory event; EFNN, explainable fuzzy neural network; NA, not applicable; ACC, accuracy.

Table 4 Characteristics of studies related to facial images

Author/year	Country	Population	Design	Diagnostic method	n	Reference standard	Model	Performance		
								AUC	Se (%)	Sp (%)
Lee RW/2009, (33)	Australia	Caucasians (95.6%)	P	Frontal and profile photographs of the head and neck	180	AHI ≥10 events/h	LR	0.82	86	59.1
							CART	0.84	70.2	87.9
Sutherland K/2016, (34)	Australia	Asian	P	Frontal and profile facial photographs	200	AHI ≥10 events/h	LR	0.76	88.6	28.3
							CART	0.81	NA	NA
Espinoza-Cuadros F/2015, (35)	Spain	N/A	P	Frontal and profile facial photographs	285	AHI ≥10 events/h	SVR	0.67	71.8	62.1
Rong Y/2019, (36)	China	N/A	P	Photos of orthotopic and oblique in the natural state	400	AHI ≥5 events/h	SVM and PCA technology, and image recognition technology	NA	74	88
						AHI ≥30 events/h		NA	80	91
Monna F/2022, (37)	France	Caucasians	P	3D maxillofacial scan	280	AHI ≥15 events/h	XGBoost	0.7	74	60

n, sample size; AUC, area under the receiver operating characteristics curve; Se, sensitivity; Sp, specificity; NA, not applicable; P, prospective cohort study; AHI, apnoea-hypopnea index; LR, logistic regression; CART, Classification and Regression Tree; SVR, support vector regression; SVM, support vector machine; PCA, principal component analysis; XGBoost, eXtreme Gradient Boosting.

models based on the frontal and profile photographs of the head and neck for the identification of OSAS using LR and Classification and Regression Tree (CART). Both methods of modeling showed good predictive ability with AUC >80%. Combined with clinical features such as witnessed apnoeas may further improve prediction. Despite the outstanding performance, researchers were required to manually mark lots of bony and cartilaginous landmarks with white tape before obtaining the photographs. Nonetheless, it was a novel attempt to suggest that facial images seemed to play a role in predicting OSAS. Caucasian OSAS patients show more obesity while Chinese OSAS patients have a more craniofacial bony restriction with the same OSAS severity (39). The same team then made another effort in Asians (34). As before, bone markers need to be manually marked prior to taking pictures. Based on the landmarks, a specific software can calculate craniofacial linear distances, angles, areas, and volumes to build prediction models. LR and CART were also used to develop the predictive models. CART analysis identified cricomental space area, mandibular width, mandibular plane angle, and neck soft tissue area as predictors for OSAS and got better performance with an AUC of 0.81.

Although the above models have achieved good accuracy, they are still not automatic enough. Considering that they required manual labeling, they are not suitable for mass screening. Espinoza-Cuadros and colleagues used an automatic landmarking method based on the Active Appearance Model (AAM) to extract a set of local craniofacial features related to OSAS including cervicomental contour area, face width, and Tragion-Ramus-Stomion Angle (35). The support vector regression (SVR) was then applied to estimate the AHI. Additional tests using estimated AHI value to classify patients with OSA (truth AHI ≥10 events/h) and without OSAS (truth AHI <10 events/h) were performed based on regression with SVR and the AUC of the model was 0.67. Combined with the clinical variables including age, height, weight, BMI, and cervical perimeter, the AUC reached 0.73 (35). This study simplified method of facial feature extraction, making it possible to screen for OSAS on a large scale by facial images.

Rong recently reported using SVM and principal component analysis (PCA) technology as well as image recognition technology to establish an algorithm based on the orthotopic and oblique photos in 400 patients, which achieved good effect, especially in patients with severe OSAS without manual labeling (36). This gives us a hint that facial images can not only help screen potential patients but can also be used to determine the severity.

Deep learning is potentially a powerful tool. It enables computational models that are composed of multiple

processing layers to learn representations of data with multiple levels of abstraction (40). Deep convolutional nets have dramatically improved facial image recognition. Lots of studies have applied deep learning to learning tasks of medical images and exhibited outstanding performance with an AUC over 0.95 in other diseases (41,42). Future researches can attempt to use deep learning techniques to train screening models for OSAS by facial images.

3D scans seem to be a good tool for characterizing maxillofacial structure. 3D photography allows the assessment of facial characteristics as an alternative to MRI (43). ML and deep learning models can be used to identify OSA patients. Recently, a study was conducted on Caucasian men to explore the predictive ability of 3D maxillofacial scans in OSAS. The 3D scans were processed by geometric morphometrics and 13 different supervised algorithms, varying from simple to more advanced, were trained and tested, with the AUC ranging from 0.62–0.70, among which, linear discriminant analysis (LDA), adaptive boosting (Adaboost), extra trees classifier, XGBoost were the most efficient. Combined with some clinical features associated with OSAS, the performance of the predictive model was slightly boosted based on the XGBoost algorithm, and the AUC reached 0.75, with a sensitivity of 80% and a specificity of 56% (37). In addition, the geometric morphometrics can reveal the difference of craniomaxillofacial features between patients with OSAS and non-OSAS population. Patients with OSAS have relatively shorter, thicker necks and stronger retrognathism as well than those in the non-OSA population.

It appears that 3D scans do not achieve the same predictive ability as 2D images, and the results are questionable due to the limited sample size and the lack of external validation as well. In addition, 3D scanning is more complex than 2D facial images. In the above trial, the entire lasted about 10 min and only 267 participants' 3D scannings can be further analyzed of the 1,251 patients originally screened (37). As a result, as 3D scannings are time-consuming and 3D scanning machines are expensive, they have the potential to explore the abnormal craniomaxillofacial features in patients with OSAS rather than a large-scale screening device. In contrast, patients' facial images appear to be a better tool for screening because of the easy accessibility of 2D facial images with ubiquitous mobile phones and deep learning algorithm. Future researches can attempt to train deep learning models for screening OSAS based on the 2D images, but it needs an enormous demand for data. In addition, whether adding the different positions of images could improve accuracy and which areas of patients' facial images are more helpful for screening are directions worth exploring as well.

Non-invasive wearable devices

PSG is a multi-sensor method, recording lots of physiological signals such as airflow, blood oxygen, respiratory effort, and electrical activity of the heart, brain, eyes, and skeletal muscles. As a result, some wearable devices with single or several sensors which vary in their range of physiological signals collected may have an effect on screening. The introduction of AI may allow the optimization of algorithms to improve the accuracy of prediction. Examples of non-invasive wearable devices are outlined in *Table 5*.

At present, some simple devices have been developed and launched on the market, and their effectiveness has been confirmed through clinical trials. Xu and colleagues developed a wearable intelligent sleep monitor (WISM) (CloudCare Healthcare Ltd., Chengdu, China) which can continuously monitor some simple signs (SaO_2, heart rate, and body movement signals) and analyse oxygen desaturation index (ODI) based on its own AI algorithm. Patients just needed to paste it on the palm, to be precise, the thenar major muscles (44). In 196 patients, the AUC was 0.95 with AHI ≥5 events/h or AHI ≥15 events/h. Using an AHI ≥15 events/h as the diagnostic criterion, the sensitivity and specificity are 92% and 89%, respectively. This wearable device might screen for OSA in a large population.

Recent studies have demonstrated that using single-lead ECG signals to train deep neural networks could extract the cardio-pulmonary features related to OSAS (49,50), which makes it possible to screen OSAS by widely-used wrist-worn Smartbands. Recently, a study explored whether wrist-worn Smartbands including Fitbit Charge4^{TM} and Fitbit AltaHR^{TM} in the consumer market could play a role in screening OSAS (45). Both of the devices were equipped with a triaxial accelerometer sensor and a photoplethysmographic sensor, which can collect patients' sleep parameters and heart rate, respectively. A multi-layer perceptron (MLP) classifier was trained to predict whether patients' AHI ≥5 events/h and the conclusion was drawn that the performance of the MLP classifier was comparable to the STOP-Bang Questionnaire which was widely used in the screening of OSAS. Considering the data collected by Wrist-Worn Smartbands was objective and convenient,

Table 5 Examples of non-invasive wearable devices

Author/year	Design	Wearable device	Collected data	n	Reference standard	Model	Performance			
							AUC	Se (%)	Sp (%)	Other
Xu Y/2022, (44)	P	WISM	Oxygen saturation, HR, body movement signals	196	AHI ≥5 events/h	NA	0.95	93	77	
					AHI ≥15 events/h		0.95	92	89	
Benedetti D/2022, (45)	P	Wrist-Worn Smartbands	HR; sleep parameters	78	AHI ≥5 events/h	MLP	NA	76.67	66.67	PPV: 88.46%
Hu X/2022, (46)	R	Snoring records	Snoring	Snore detection dataset >4,600 min	NA	ARF	NA	NA	NA	
Cho SW/2022, (47)	P	Smartphone	Snoring	423	AHI ≥5 events/h	RF	0.90	90.8	64.7	ACC: 88.2%
					AHI ≥15 events/h		0.89	87.3	70.6	ACC: 82.3%
					AHI ≥30 events/h		0.90	83	80.3	ACC: 81.7%
Wei Y/2018, (48)	P	Wearable device based on bone conduction microphone	Snoring	10	Patients have been diagnosed by PSG	HMM	NA	NA	NA	

n, sample size; AUC, area under the receiver operating characteristics curve; Se, sensitivity; Sp, specificity; P, prospective cohort study; R, retrospective; WISM, wearable intelligent sleep monitor; HR, heart rate; AHI, apnoea-hypopnea index; NA, not applicable; PSG, polysomnography; MLP, multi-layer perceptron; ARF, auditory receptive field; RF, random forest; HMM, hidden Markov model; PPV, positive predictive value; ACC, accuracy.

they have the potential to serve a population-scale screening for OSAS. In children and adolescents, Fitbit Ultra (51), Fitbit Charge 2™ (52), and other commercial Wrist-Worn Smartbands (53) failed to provide clinically comparable results to PSG and should be used with caution. Considering that they were not originally designed to screen for OSAS, the built-in accelerometer, as well as the algorithm, need to be updated to get a better prediction effect.

Snoring, which is one of the most common symptoms of OSAS carries a lot of physiological information about the upper airway and sleep (54), so researchers are devoted to studying its value in predicting OSAS for decades. A past study has demonstrated that Maximal frequency (Fmax) and average snoring sound intensity level (SSIL) of snoring are related to AHI and severity of OSAS (55). Azarbarzin and colleagues reported that snoring sound segments extracted such as average power and zero crossing rate have the potential to identify OSAS patients, with an accuracy of 96.4% (56).

Voice recording equipment is easy to get access, making it possible that snore detection by portable devices could be a promising tool for screening OSAS. Different from the conventional snore detection approaches in the previously described literature, the introduction of AI could provide more robustness and accuracy. There are different classification approaches for snoring analysis such as higher-order-spectra (HOS) (57), Gaussian mixture model (58), SVM (59), and artificial neural network (60). A recent study proposed a novel end-to-end deep learning model based on snoring recorded from wearable devices. This model combines detection information at various levels of feature maps and auditory receptive field (ARF) modules to mimic the characteristics of the responses of the auditory system to sound frequencies. The model was evaluated in a snore detection dataset with more than 4,600 min and outperformed other traditional approaches (46). However, this model has not been validated in patients, and its ability to screen for OSAS remains unknown.

Sometimes a specific microphone is not even needed,

the built-in microphone of the smartphone can achieve the screening effect. A study carried in 423 patients used an RF algorithm to create an accurate OSAS prediction model with smartphone-recorded breathing sounds without denoised during sleep. For an AHI threshold of 5, 15, and 30 events/h, the AUC were 0.90, 0.89, and 0.90, respectively (47).

A based on bone conduction microphone was used in collecting snoring. Compared to the air conduction microphone, it is less susceptible to ambient noise and rolls over during sleeping. A study on a small sample of patients has confirmed the feasibility of this kind of device. Hidden Markov models (HMMs) were employed to train the model by extracting Mel-Frequency Cepstral Coefficients (MFCC) vectors as features of the sounds (48). It can detect apnoea or hypopnea part without external influence, which may optimize the accuracy of screening by snoring detection.

Ongoing studies are exploring various simplified technologies for screening OSAS to determine the possible population, reducing the dependence on PSG. Wearable devices provide the opportunity to collect different types of data non-invasively and continuously for long-term sleeping. Future studies can explore the combination of several approaches such as heart rate and snoring to improve the screening accuracy of the model.

Conclusion and future perspective

AI has the potential to screen patients with OSAS on a mass scale. It enables population-level screening using automated analysis of large volumes of data including anthropometric data alone or combined with some simple physiological signals which are easy to get, patients' facial images and 3D scanning, and some intelligent wearable devices as well. While these screening tools cannot achieve the diagnosis, they can screen out suitable people for subsequent PSG to reduce the medical burden. Furthermore, these intelligent screening tools allow anesthesiologists to identify OSAS in patients who are scheduled for surgery during routine preoperative visits so that anesthesiologists can optimize preoperative preparation and work out a specific anesthesia plan to reduce complications. Considering the current performance and the availability of data, the prediction models based on anthropometric data combined with some simple physiological signals have more potential to become a feasible screening tool preoperatively. Although all the models mentioned above have achieved relatively good performance, it is still unknown whether they can be extended to large-scale populations in the community as they haven't been prospectively verified in large-scale populations. Furthermore, a multimodal model can be designed based on clinical features, facial images, and some single-sensor wearable devices which can be integrated into a simple medical device, or even a smartphone app for mass screening.

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Footnote

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