



# Sleep-Disordered Breathing: Diagnosis

# 5

Daniel Álvarez, Andrea Crespo, Leila Kheirandish-Gozal, David Gozal, and Félix del Campo

## 5.1 Diagnostic Procedures

### History and Physical Examination

The diagnosis of OSA starts with a sleep history, which commonly gathers data from three complementary approaches: (1) evaluation of OSA-related symptoms, (2) sleep habit evaluation, and (3) comprehensive evaluation of high-risk patients due to potential negative consequences. OSA is a complex disease and thus patients can manifest a large spectrum of different symptoms. Commonly, adult patients with OSA report loud snoring, witnessed apneas, awakenings with choking sensation, and excessive daytime sleepiness, the latter usually assessed by the Epworth Sleepiness Scale (ESS) [1]. Other common symptoms are nonrefreshing sleep, tiredness, morning headaches, and neurobehavioral problems [2]. On the other hand, a less common phenotype includes insomnia and fatigue as predominant

---

D. Álvarez (✉) · F. del Campo (✉)  
Biomedical Engineering Group, University of Valladolid, Valladolid, Spain

Pneumology Department, Río Hortega University Hospital, Valladolid, Spain

Centro de Investigación Biomédica en Red – Bioingeniería, Biomateriales y Nanomedicina (CIBER-BBN), Madrid, Spain

e-mail: [dalvarezgo@saludcastillayleon.es](mailto:dalvarezgo@saludcastillayleon.es); [fcampoma@saludcastillayleon.es](mailto:fcampoma@saludcastillayleon.es)

A. Crespo

Biomedical Engineering Group, University of Valladolid, Valladolid, Spain

Pneumology Department, Río Hortega University Hospital, Valladolid, Spain

e-mail: [acrespos@saludcastillayleon.es](mailto:acrespos@saludcastillayleon.es)

L. Kheirandish-Gozal · D. Gozal

Department of Child Health and the Child Health Research Institute, University of Missouri School of Medicine, Columbia, MO, USA

e-mail: [gozall@health.missouri.edu](mailto:gozall@health.missouri.edu); [gozald@health.missouri.edu](mailto:gozald@health.missouri.edu)

symptoms, which is more particularly encountered in women. It is important to highlight that, due to subjectivity, there is a great variability among patients concerning the prevalence of symptoms, particularly sleepiness [3]. In children, the emergence of symptoms is much more subtle, even if younger patients are more susceptible to develop morbid consequences. As such, snoring may be the only symptom that parents may report, or snoring may be apparent along with snorting or gasping episodes, restless sleep, bedtime wetting, frequent nightmares or night terrors, bruxism, morning headaches, grumpy awakenings, tiredness, falling asleep in school or in the car, and problematic progression in academic performance at school. A particular feature of children who are at risk for sleep-disordered breathing is the presence of inattention with or without hyperactivity, the latter being much more frequent among non-obese children. As such, the concept of different phenotypes based on clinical presentation has been proposed to include type I (non-obese, hyperactive) and type II (obesity and excessive daytime sleepiness with inattention). Furthermore, social withdrawal and aggressive or oppositional defiant behaviors are also common.

Besides symptoms, major indicators of OSA include hereditary factors (family history of the disease) and known anthropometric factors linked with increased risk for upper airway obstruction, such as oropharyngeal and nasal abnormalities, large neck circumference, increased body mass index (BMI), or additional markers of obesity [2, 4]. In addition, cardiorespiratory, cerebrovascular, and metabolic comorbidities potentially linked with OSA should be investigated [5]. Table 5.1 summarizes sleep assessment procedure, whereas Table 5.2 shows criteria for OSA diagnosis according to the American Academy of Sleep Medicine (AASM) [6].

**Table 5.1** Sleep evaluation in the diagnosis of OSA [4]

High-risk patients	<ul style="list-style-type: none"> <li>– Obesity (BMI &gt;35)</li> <li>– Congestive heart failure</li> <li>– Atrial fibrillation</li> <li>– Treatment refractory hypertension</li> <li>– Type 2 diabetes</li> <li>– Stroke</li> <li>– Nocturnal dysrhythmias</li> <li>– Pulmonary hypertension</li> <li>– High-risk driving populations</li> <li>– Preoperative for bariatric surgery</li> </ul>
Symptoms of OSA	<ul style="list-style-type: none"> <li>– Snoring</li> <li>– Witnessed apneas</li> <li>– Gasping/choking episodes at night</li> <li>– Excessive sleepiness not explained by other factors</li> <li>– Nonrefreshing sleep</li> <li>– Nocturia</li> <li>– Morning headaches</li> <li>– Sleep fragmentation/sleep maintenance insomnia</li> <li>– Decreased concentration and memory</li> <li>– Decreased libido</li> <li>– Irritability</li> </ul>

**Table 5.1** (continued)

Suggested features of OSA	<ul style="list-style-type: none"> <li>– Increased neck circumference (&gt;17 inches in men, &gt;16 inches in women)</li> <li>– BMI <math>\geq</math> 30 kg/m<sup>2</sup></li> <li>– A modified Mallampati score of 3 or 4</li> <li>– Retrognathia</li> <li>– Lateral peritonsillar narrowing</li> <li>– Macroglossia</li> <li>– Tonsillar hypertrophy</li> <li>– Elongated/enlarged uvula</li> <li>– High arched/narrow hard palate</li> <li>– Nasal abnormalities (polyps, deviation, valve abnormalities, turbinate hypertrophy)</li> <li>– Overjet</li> <li>– Musculoskeletal abnormalities</li> </ul>
---------------------------	--

*BMI* body mass index, *OSA* obstructive sleep apnea

**Table 5.2** Criteria for OSA diagnosis [6]

Diagnosis of OSA	Parameters				
A + B criteria	A	Presence of $\geq$ 1 symptoms or diseases			
		<ul style="list-style-type: none"> <li>– Sleepiness</li> <li>– Nonrestorative sleep</li> <li>– Fatigue</li> <li>– Insomnia</li> </ul>	<ul style="list-style-type: none"> <li>– Breath holding</li> <li>– Gasping</li> <li>– Choking</li> </ul>	<ul style="list-style-type: none"> <li>– Snoring and/or</li> <li>– Breathing interruptions</li> </ul>	<ul style="list-style-type: none"> <li>– Hypertension</li> <li>– Mood disorder</li> <li>– Cognitive dysfunction</li> <li>– Coronary artery disease</li> <li>– Stroke</li> <li>– Congestive heart failure</li> <li>– Atrial fibrillation</li> <li>– Type 2 diabetes mellitus</li> </ul>
	B	Polysomnography or home sleep apnea testing			
		– $\geq$ 5 predominantly obstructive respiratory events per hour			
C criteria		Polysomnography or home sleep apnea testing			
		– $\geq$ 15 predominantly obstructive respiratory events per hour			

*OSA* obstructive sleep apnea

For children, it is important to follow the guidelines as formulated by various professional societies [7–9]. More generally, adoption of the concept of habitual snoring (defined as snoring recognized by caretakers at least 3 nights per week, particularly if loud) that also exhibits an additional problematic symptom is an excellent rule of the thumb to make the decision to evaluate further with some objective diagnostic testing.

## OSA Screening Questionnaires

Major advantages of questionnaires are readiness and negligible cost. However, clinical questionnaires are not recommended as single tools for OSA diagnosis due to their limited accuracy. Nevertheless, despite their low specificity (large number of false-positive cases) [10, 11], standardized questionnaires show overall high sensitivity, and thus they can be useful for screening purposes. Accordingly, questionnaires can be easily performed in clinical practice to identify patients with higher risk for OSA both in primary care and in specialized care. Some authors suggest their usefulness in low-income countries where PSG is not available [12].

There are several standardized questionnaires aimed at assisting physicians in the detection of OSA. The Berlin questionnaire (BQ) [13], OSA50 [14], and STOP-BANG [15] are probably the most popular, while No-apnea, GOAL, NoSAS, and Obstructive Airway Adult Test (OAAT) [16] have been also widely assessed [17–26]. There are few studies comparing the diagnostic ability of these questionnaires with each other, and some inconsistencies have been reported [12, 27]. Table 5.3 shows the most widely used questionnaires.

**Table 5.3** Main questionnaires used for identifying patients with a high pretest probability of OSA [10]

Questionnaire	Initially developed	Parameters	Level of OSA risk	Diagnostic accuracy (AHI > 15 events/h)
Berlin Questionnaire	Primary care	10 questions pertaining to the following 3 categories – Snoring – Daytime sleepiness – Hypertension	<ul style="list-style-type: none"> <li>• <i>High</i>: <math>\geq 2</math> categories with positive score</li> <li>• <i>Low</i>: 1 or no categories with positive score</li> </ul>	<ul style="list-style-type: none"> <li>• <i>Sensitivity</i>: 0.77 (0.73–0.81)</li> <li>• <i>Specificity</i>: 0.44 (0.38–0.51)</li> </ul> Assessed in [12]
STOP-BANG Questionnaire	Surgical patients at preoperative clinics	4 questions (yes/no) regarding the following signs/symptoms – Snoring – Tiredness – Observed apneas or choking – High blood pressure Plus 4 clinical attributes (yes/no) – Obesity (BMI >35 kg/m <sup>2</sup> ) – Age (>50 years) – Neck circumference (>40 cm) – Male gender	<ul style="list-style-type: none"> <li>• <i>High</i>: score of 5–8</li> <li>• <i>Intermediate</i>: score of 3–4</li> <li>• <i>Low</i>: score of 0–2</li> </ul>	<ul style="list-style-type: none"> <li>• <i>Sensitivity</i>: 0.90 (0.86–0.93)</li> <li>• <i>Specificity</i>: 0.36 (0.29–0.44)</li> </ul> Assessed in [12]

**Table 5.3** (continued)

Questionnaire	Initially developed	Parameters	Level of OSA risk	Diagnostic accuracy (AHI > 15 events/h)
OSA50	Primary care	Four components (yes/no) – Age $\geq$ 50: yes 2 points – Snoring: yes 3 points – Witnessed apneas: yes 2 points – Waist circumference (>102 cm male; >88 cm female): yes 3 points	High risk $\geq$ 5 points	Sensitivity: 0.94 Specificity: 0.31 • Assessed in [14]

AHI apnea-hypopnea index, BMI body mass index, OSA obstructive sleep apnea

In children, a large number of questionnaires have also been developed over the years with overall remarkable similarity in their performance even if some are better than others. These questionnaires for the most part exhibit excellent sensitivity but relatively lower specificity, making them robust tools for screening purposes but not accurate enough to be used as an alternative to a diagnostic test [28–33].

More complex multivariate predictive models for OSA have been proposed, including a variety of additional symptoms (infections, high blood pressure, attention deficits) and measures (palatal height, maxillary, and mandibular intermolar distances). Despite these models demonstrated higher ability to discriminate OSA, particularly for higher diagnostic thresholds for the disease, they still show a great imbalance between sensitivity and specificity, leading to a marginal use in clinical practice [23].

## Comprehensive Sleep Studies

History and questionnaires provide physicians with relevant information on the presence or absence of the disease. Nevertheless, definitive diagnosis of OSA must be confirmed using appropriate devices for comprehensive sleep testing [10]. Table 5.4 summarizes the four traditional categories of devices for sleep analysis according to the complexity (number of physiological signals involved) and the setting (supervised vs. unattended) [34]. These approaches are applicable to both adults and children with some caveats that will be addressed below.

**Table 5.4** Main characteristics of equipment used in the different approaches for adult OSA diagnosis according to AASM [10, 34]

Category	Site	Channels	Advantage	Disadvantage	Recommendation
Type I or PSG	Attended, inside sleep laboratory	$\geq 7$ data (EEG, EOG, EMG, ECG and respiratory channels) (typically $\geq 16$ )	Sleep parameters	<ul style="list-style-type: none"> <li>– High cost</li> <li>– Complex</li> <li>– Limited availability</li> <li>– Patient inconvenience</li> <li>– Disturb sleep quality</li> <li>– Intrusive</li> <li>– Time-consuming</li> </ul>	<ul style="list-style-type: none"> <li>– Moderate-to-high probability of OSA without comorbidity (strong)</li> <li>– Low-to-moderate probability of OSA</li> <li>– Patients with significant diseases, suspected CSA, or hypoventilation (strong)</li> <li>– Suspected other sleep disorders than OSA</li> <li>– Nondiagnostic HSAT and suspected OSA (strong)</li> <li>– Initial PSG negative and suspected OSA (weak)</li> </ul>
Type II or Home PSG	Unattended, outside sleep laboratory	$\geq 7$ data (EEG, EOG, EMG, ECG, and respiratory channels) (typically $\geq 16$ )	<ul style="list-style-type: none"> <li>– Sleep parameters</li> <li>– Lower cost than Type I</li> <li>– Improved sleep quality</li> <li>– Preferred by the patient</li> </ul>	<ul style="list-style-type: none"> <li>– Intrusive</li> <li>– Time-consuming</li> <li>– Relative lack of portable devices</li> </ul>	<ul style="list-style-type: none"> <li>– Predominantly for research purposes</li> <li>– Further studies are needed</li> </ul>
Type III or RP	Unattended, outside sleep laboratory	$3 \leq$ channels $< 7$ (airflow, snoring, respiratory excursion, body position, heart rate, oxygen saturation)	<ul style="list-style-type: none"> <li>– More accessibility</li> <li>– Lower cost and workload than types I and II</li> <li>– More comfortable and convenient for patients</li> </ul>	<ul style="list-style-type: none"> <li>– Not sleep parameters</li> <li>– Relative lack of portable devices</li> </ul>	<ul style="list-style-type: none"> <li>– Moderate-to-high probability of OSA without comorbidity (strong)</li> <li>– Unable to perform PSG because of immobility or infirmity</li> <li>– Confirm treatment efficacy</li> </ul>

(continued)

**Table 5.4** (continued)

Category	Site	Channels	Advantage	Disadvantage	Recommendation
Type IV	Unattended, outside sleep laboratory	<3 (oxygen saturation and heart rate, or just air flow)	<ul style="list-style-type: none"> <li>– Easy interpretation</li> <li>– More accessibility than type III</li> <li>– Lower cost than type III</li> </ul>	Lack of information about many sleep and respiratory parameters	Screening OSA in moderate-to-high probability

*ECG* electrocardiogram, *EEG* electroencephalogram, *EMG* electromyogram, *EOG* electrooculogram, *HSAT* home sleep apnea testing, *OSA* obstructive sleep apnea, *PSG* polysomnography, *RP* respiratory polygraphy

### Polysomnography

In-laboratory polysomnography (PSG) is the gold standard method for OSA diagnosis. PSG provides essential information on the duration and quality of sleep, sleep stages, and transient events (electroencephalographic, muscular, cardiac, and respiratory events) during sleep. Current AASM guidelines [35] delineate scoring and interpretation rules as well as technical aspects concerning PSG performance and analysis based on cumulative published evidence.

Electroencephalographic channels and associated recordings (electrooculogram and electromyogram) are an essential part of a PSG. EEG, EOG, and EMG signals are used to analyze the macro- (sleep stages) and micro- (electroencephalographic events) structure of sleep. Table 5.5 summarizes the main characteristics of sleep stages and common electroencephalographic events [35].

Cardiorespiratory recordings involving airflow, respiratory movements, electrocardiogram, pulse oximetry, and body position compose the second main part of a PSG, aimed at characterizing and quantifying respiratory events. Monitoring snoring and hypoventilation are optional in adults but is required in children, particularly assessment of alveolar hypoventilation since many children may manifest sleep-disordered breathing almost exclusively by developing extended periods of elevated carbon dioxide levels during sleep. Table 5.6 shows the types and definition of polysomnographic respiratory events involved in the diagnosis of sleep-disordered breathing in adults [35]. Additional physiological recordings have been proposed to be included in the PSG, such as the divided nasal cannula [36]. However, no improvement was found in terms of the accuracy of AHI.

In order to obtain reliable and confident diagnosis, the AASM recommends a minimum of 4 h of total sleep time (6 h for children) for high-risk patients undergoing PSG, while this limit increases to 6 h (and >16% of total sleep time REM sleep in children) in clinical trials in order to account for a potentially broader spectrum of OSA severity [3].

OSA severity is categorized according to the AHI, which accounts for the combined number of apneas and hypopneas per hour of sleep. Although the most appropriate diagnostic threshold for positive OSA has been under great discussion for

**Table 5.5** Main characteristics of states and electroencephalographic events during sleep [35]

Scoring	Definitions
W	<ol style="list-style-type: none"> <li>1. Alpha rhythm (posterior dominant rhythm); occipital region with eye closure, attenuating with eye opening</li> <li>2. Eye blinks: vertical eye movements at 0.5–2 Hz</li> <li>3. Reading eye movements: slow phase followed by rapid phase</li> <li>4. REM: irregular; lasting &lt;500 ms</li> <li>5. SEM: more regular; lasting &gt;500 ms</li> </ol>
N1	<ol style="list-style-type: none"> <li>1. SEM: more regular; lasting &gt;500 ms</li> <li>2. LAMF: 4–7 Hz (theta)</li> <li>3. V waves: 0.5 s in Central region</li> <li>4. Sleep onset: first epoch of any stage other than W, usual N1</li> </ol>
N2	<ol style="list-style-type: none"> <li>1. K complex: well-delineated, negative sharp wave immediately followed by a positive component standing out from the background EEG; duration &gt;0.5 s; maximal in the frontal region</li> <li>2. Sleep spindle: train of distinct sinusoidal waves 11–16 Hz and duration &gt;0.5 s; maximal in the central region</li> </ol>
N3	<ol style="list-style-type: none"> <li>1. Slow wave activity (0.5–2 Hz) and &gt;75 <math>\mu</math>V; frontal region</li> </ol>
REM	<ol style="list-style-type: none"> <li>1. REM: irregular; lasting &lt;500 ms</li> <li>2. Low chin EMG tone: baseline no higher than any other sleep stage and usually lowest level of the entire recording</li> <li>3. Saw-tooth waves: trains of sharply contoured or triangular, often serrated, 2–6 Hz waves; maximal over central region; may precede a burst of REM</li> <li>4. Transient muscle activity: short, irregular burst of EMG &lt;0.25 s; superimposed on low EMG chin or leg tone</li> </ol>
Major body movements	<ol style="list-style-type: none"> <li>1. Movement or muscle artifact obscuring the EEG for more than half an epoch to the extent that the sleep stage cannot be determined</li> <li>2. If alpha rhythm is present, even &lt;15 s, score Wake</li> <li>3. If no alpha rhythm is discernable, but the epochs before or after is scored as W with major body movements, score as stage W</li> <li>4. Otherwise, score the epoch as the same stage as the epoch that follows it</li> </ol>
Arousal	<ol style="list-style-type: none"> <li>1. Abrupt shift of EEG frequency including alpha, theta and/or frequencies above 16 Hz</li> <li>2. At least 3 s long</li> <li>3. Must have 10 s of stable sleep preceding the change</li> <li>4. During REM requires a concurrent increase in submental EMG for at least 1 s</li> </ol>

*EEG* electroencephalogram, *EMG* electromyogram, *LAMF* low-amplitude mixed frequency, *REM* rapid eye movements, *SEM* slow eye movement, *V waves* vertex sharp waves

years, currently, the following severity degrees are widely accepted in adults [10]: mild OSA,  $5 \leq \text{AHI} < 15$  events/h; moderate OSA,  $15 \leq \text{AHI} < 30$  events/h; and severe OSA  $\text{AHI} \geq 30$  events/h. Because the collapsibility of the upper airway is lower in children than in adults, the number of respiratory events in healthy children is <0.5 events/h of sleep. Accordingly, the criteria for OSA severity have traditionally been adopted as follows: >1–5 events/h corresponds to mild OSA; >5 to 10 events/h represent moderate OSA and >10 events/h is viewed as severe OSA in the pediatric age. However, for children older than 14 years of age, application of adult or pediatric OSA severity criteria is at the discretion of the physician.



**Table 5.6** Scoring criteria for respiratory events in adults [35]

Event	Definitions	
Apnea	>90% drop from baseline; for at least 10 s	
	Obstructive	Continued or increased inspiratory effort throughout event
	Central	Absent inspiratory effort throughout event
	Mixed	Absent of inspiratory effort for first part of event followed by resumption of inspiratory effort in the second portion of event
Hypopnea		All criteria are needed – >30% drop from baseline; for at least 10 s – >3% desaturation from pre-event baseline or arousal; >4% desaturation from pre-event baseline
	Obstructive (optional)	All criteria are needed: snoring, increased inspiratory flattening, paradox appears
	Central (optional)	None of the criteria appears: snoring, increased inspiratory flattening, paradox appears
RERA (optional)	Sequence of breath lasting at least 10 s lead an arousal that shows – Increased respiratory effort – Flattening of the inspiratory portion of signal Must not qualify for apnea of hypopnea	
Hypoventilation (optional)	Either of the next occur – Increase in arterial PCO <sub>2</sub> to a value >55 mmHg for >10 min – >10 mmHg increase in arterial PCO <sub>2</sub> during sleep and exceeds 50 mmHg for >10 min	
Cheyne-Stokes	Both of the next criteria occur – Episodes of >3 consecutive central apnea or central hypopnea separated by a crescendo and decrescendo change in breathing amplitude within a cycle of >40 s – Episodes of >5 central apnea or central hypopnea per hour of sleep associated with crescendo/decrecendo breathing pattern recorded for over 2 h of monitoring	
AHI	Number of apneas and hypopneas per hour of total sleep time	
RDI	AHI with the addition of RERAs per hour of sleep during polysomnography	
REI	Number of apneas and hypopneas per hour of total recording time on home monitoring devices for sleep apnea	

*AHI* apnea-hypopnea index, *RDI* respiratory disturbance index, *REI* respiratory event index, *RERA* respiratory effort-related arousal

Despite been the standard index to diagnose OSA, the AHI does not completely reflect the complex heterogeneity of the disease. Its main drawback is related to its inability to differentiate among the clinical phenotypes of OSA [3] or predict all negative consequences of the disease [2]. Similarly, it has been found that different measures of hypoxia are better predictors of outcomes and adverse events than the AHI [37]. However, notwithstanding the limitations of AHI regarding more precise patient phenotyping, severity-dependent associations between AHI and some of the common morbid consequences of OSA have been detected despite the marked heterogeneity of morbid phenotype [38], whereby other morbidities do not exhibit significant associations with AHI [39].

In the same regard, PSG has widely known limitations. It is complex, time-consuming, and intrusive for patients. In addition, regarding equipment and

specialized staff, PSG is costly leading to limited accessibility and availability. Therefore, due to the high prevalence of the disease worldwide, it is not a cost-effective approach to evaluate all patients suspected of suffering from the disease. Accordingly, simplified alternatives are being sought, particularly to conduct portable sleep studies at home and under the lead assumption that such transition to home will not curtail the accuracy and reliability of the alternative tests.

### Home Sleep Apnea Testing

In recent years, abbreviated and portable at-home sleep apnea testing (HSAT) has emerged as an alternative or complementary diagnostic tool for OSA. There is a great number of commercial devices currently available. In 2007, the AASM established the characteristics and minimum requirements of HSAT devices [40]. Their use as an alternative to standard PSG was subsequently accepted only in uncomplicated patients showing high pretest probability for the disease [18, 40].

Concerning the physiological signals recorded by abbreviated HSAT devices, three signals are considered relevant and widely recommended: blood oxygen saturation from oximetry, respiration from nasal pressure or alternatively respiratory bands, and heart rate from ECG or from the pulse oximetry signal.

The implementation of HSAT procedures differs among countries. In Europe, simplified portable monitoring has been widely accepted, firstly supervised in the hospital setting and then unattended at home [41]. Similarly, up to 40% of total patients are referred to HSAT in Canada [42]. In contrast, routine HSAT use in the patient's home in the USA has been slower to be adopted due to some regional limitations related to reimbursement and personnel structure. As no EEG is recorded, abbreviated HSAT devices do not provide information about sleep, nor do these recordings provide sleep time or arousals, which limits their ability for ruling out the disease [10]. Therefore, the numerator of events does not include arousals and the denominator is larger since it denotes total recording time (TRT), while PSG actually includes total sleep time (TST; obviously  $TRT > TST$ ), such that unless the disease is more severe, there can be clear underestimations or mis-estimations in any given patient. Indeed, a remarkable overall underestimation (high false-negative rate) has been consistently reported [43–45]. Accordingly, in-lab PSG or further follow-up should be considered when HSAT results are negative. Therefore, the cost associated with repeated test due to false-negative results (17%) [40] and technical failures (18%) [46] must be taken into account [47]. The main limitations of HSAT are summarized in Tables 5.7 and 5.8. These limitations of HSAT are further magnified in pediatric settings, because the severity criteria are much more stringent and the numerator to calculate the AHI is much smaller [50].

Conversely, the main advantages include less cost and less intrusiveness for patients. Particularly, higher cost-effectiveness ratio of HSAT compared to in-lab PSG has been reported in appropriately selected patients [51–55]. In regard to patient's comfort, contradictory data have been recently reported [56, 57]. "Real-world" studies are needed to prospectively assess preferences and satisfaction of patients with HSAT. Additionally, reduced workload in sleep laboratories and reduced waiting times for diagnosis and treatment are commonly reported benefits for both specialists and patients. Finally, HSAT enables multiple-night assessment

**Table 5.7** Limitations of HSAT leading to OSA underestimation [48]

Limitations of HSAT	
RDI is calculated using TRT instead of TST: TRT is higher than TST, leading to underestimation	
No measure of REM sleep: OSA underestimation in patients with REM-predominant OSA	
No measure EEG arousals: OSA underestimation if hypopneas associated only with arousal	
Less supine time sleep at home compared with sleep lab setting: OSA underestimation in patients with supine-predominant OSA	
Self-placement of sensors can be cumbersome and confusing, leading to poor-quality recordings	
The home environment may be less conducive to sleep than the sleep lab if there are environmental disturbances to sleep	

*EEG* electroencephalogram, *OSA* obstructive sleep apnea, *RDI* respiratory disturbance index, *REM* rapid eye movement, *TRT* total recording time, *TST* total sleep time

**Table 5.8** Factors affecting suitability of HSAT [49]

Patient-related factors	<ol style="list-style-type: none"> <li>1. Neuropsychological</li> <li>2. Severe physical disability with inadequate care attendance</li> <li>3. Unsuitable home environment</li> <li>4. Discretionary</li> </ol>
Sleep disorder-related factors	<ol style="list-style-type: none"> <li>1. Consideration of other sleep disorders: central sleep apnea, hypoventilation, heart failure, neurological disorders, sleep-related movement disorder, parasomnia or seizure disorder, unexplained hypersomnolence</li> <li>2. Video confirmation of body positional, rotational aspects or other associated movements</li> </ol>

at a reasonable cost, minimizing the confounding effect of the widely known night-to-night variability of OSA [3].

Concerning the different types of HSAT approaches (Table 5.4), comparable clinical (BMI, ESS, blood pressure) and treatment (CPAP adherence) outcomes have been reported in OSA patients diagnosed using ambulatory PSG (type II) compared to in-hospital standard diagnosis [58]. Despite more limited cardiopulmonary data, respiratory polygraphy (RP) (type III) is able to expedite diagnosis [53]. Similarly, it has been found useful to increase availability of both diagnosis and treatment resources in patients with mobility issues and major illness [10]. A major meta-analysis on the effectiveness of type III monitors reported good diagnostic performance (AUC ranging from 0.85 to 0.99) for the common OSA severity cut-offs and no significant differences in clinical management parameters between patients diagnosed using either PSG or type III monitoring [53]. In the context of children, the jury is still out and the consensus at this stage pending additional large-scale studies is still in favor of minimizing the use of HSAT and preferably conducting PSG unless the regional circumstances and resources lead to substantial delays in diagnosis [59–61].

Accurateness and reliability of more simplified devices (type IV) are still under debate, particularly single-channel blood oxygen saturation (SpO<sub>2</sub>) from oximetry. Respiratory disturbance index (RDI) from RP and oxygen desaturation index (ODI) from oximetry have been found to provide similar predictions of actual AHI, showing small differences compared to the known night-to-night variability [62].

Nevertheless, the AASM demands further evidence on the efficiency of unattended oximetry and similar single-channel approaches as reliable tools for OSA diagnosis (currently recommended only for screening purposes), particularly in mild or asymptomatic patients and in the presence of other sleep disorders (central sleep apnea) or significant concomitant diseases [10]. Concerning cardiorespiratory comorbidities, several studies have assessed the usefulness of simplified screening tests for OSA in patients with hypertension [63], heart failure [64], and stroke [65]; in the presence of COPD [66, 67] or morbid obesity [68]; in patients remitted for surgery [69]; and in hospitalized elders [70].

The interest on oximetry recently increased due to its ability to characterize intermittent hypoxia. Several studies reported that hypoxia level correlates with mortality, cardiovascular outcomes, and cancer incidence better than the standard AHI [3, 71–73]. In this regard, novel oximetric indices have been proposed to parameterize intermittent hypoxia linked with OSA, such as the hypoxic burden [73], the hypoxia load [71], or the desaturation severity parameter [74].

A similar evolutionary trend has occurred in the context of pediatric settings. The Oxygen Desaturation ( $\geq 3\%$ ) Index (ODI3) and McGill Oximetry Score (MOS) are widely used as predictors of moderate-to-severe OSA (apnea-hypopnea index-AHI  $> 5$  episodes/h), an indication for adenotonsillectomy [75, 76]. In a recent study, we have shown that the optimal cutoff values for the ODI3 and MOS were  $\geq 4.3$  episodes/h and  $\geq 2$ , respectively. Nevertheless, the ODI3 emerged as the better performing index for detecting moderate-to-severe OSA in habitually snoring children when PSG is not available [77].

### **Blood Biomarkers**

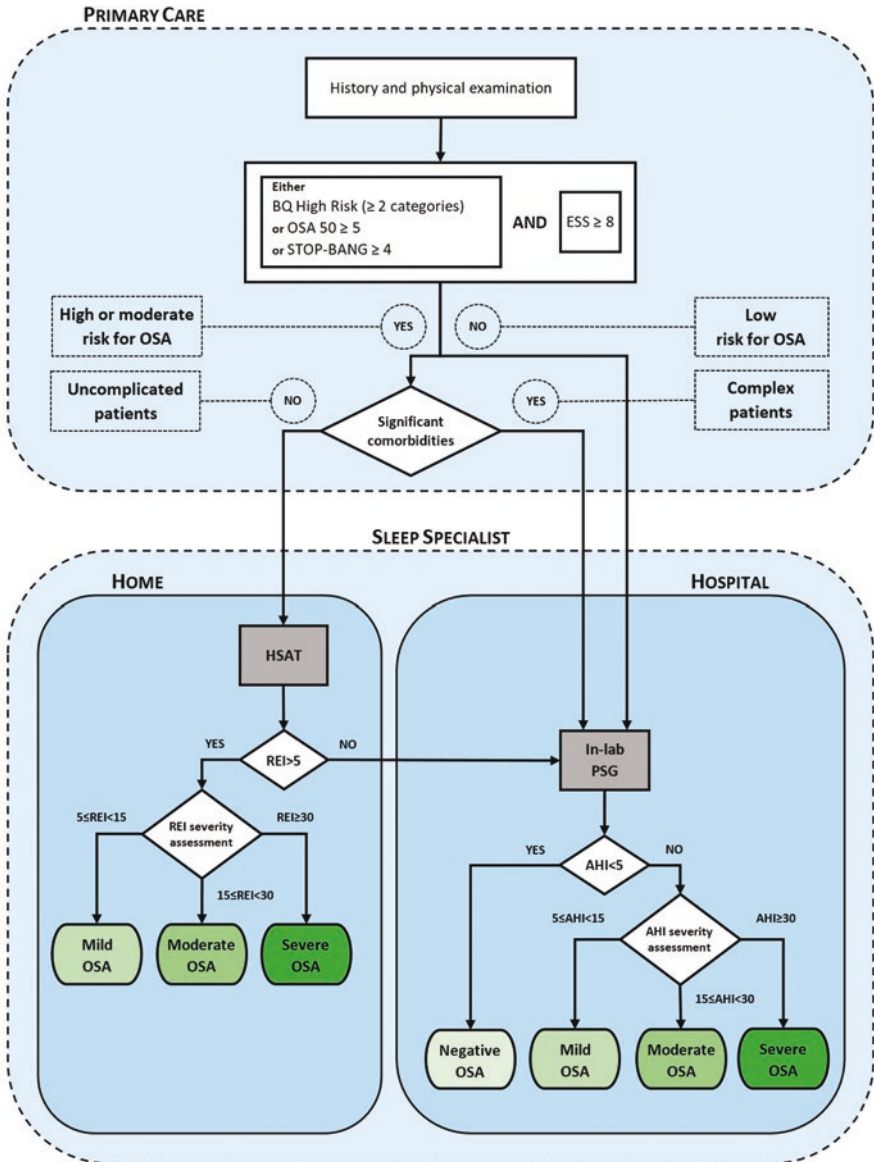
Sleep apnea is known to trigger mechanisms leading to metabolic and endocrine dysfunctions, such as inflammation, hypoxemia, and oxidative stress, which can be readily detected by blood tests. Accordingly, blood biomarkers have been proposed to enhance the diagnosis of OSA [10, 78]. Common biomarkers are glycated hemoglobin (HbA1c), C-reactive protein (CRP), erythropoietin (EPO), interleukin-6 (IL-6), and uric acid [78]. Similar efforts in children have yielded remarkable accuracy under specific circumstances in the detection of disease, in the identification of residual OSA after treatment, or in the evaluation of comorbidities associated with OSA [79–85].

Some biomarker combinations have been found to correlate with sleep apnea severity, emerging as potential user-friendly and low-cost tools for OSA screening in high-probability patients [86–90]. Nevertheless, further research is encouraged in this topic to obtain successful diagnosis and treatment strategies, mainly by means of big data and machine learning techniques [3, 91].

---

## **5.2 Diagnostic Strategy**

As mentioned above, attended in-lab overnight PSG is the gold standard tool for OSA diagnosis. Nevertheless, due to the widely known drawbacks of PSG and the increased frequency of visits linked with suspected sleep apnea, the aforementioned



**Fig. 5.1** Flowchart summarizing the diagnostic strategy for OSA detection involving primary care, HSAT and in-laboratory PSG

simplified methods have been implemented within the diagnostic protocols in order to conduct sleep studies at home, reduce costs and waiting lists, and expedite both diagnosis and treatment. Figure 5.1 shows a flowchart with the diagnostic strategy for OSA detection according to the current evidence and recommendations.

The main recommendations to conduct standard PSG in a sleep laboratory are:

- Patients with significant comorbidities (such as severe pulmonary disease, congestive heart failure, or neuromuscular weakness)
- Patients with risk of central or mixed sleep apnea or other sleep disorders
- Patients with low probability of OSA
- Pediatric patients except for resource-constrained settings

Currently, according to the AASM, HSAT is a suitable alternative to in-lab PSG for the diagnosis of OSA in patients showing moderate-to-high pretest probability without certain comorbidities [10]. Positive OSA is diagnosed in patients showing symptoms and AHI/RDI/REI  $\geq 5$  events/h from PSG or HSAT or, alternatively, AHI/RDI/REI  $\geq 15$  events/h regardless of symptoms (Table 5.2).

The scarcity of sleep specialists and sleep units forces primary care to increase its role in the detection of OSA [92]. In this framework, general practitioners have two possible pathways to manage patients in order to speed up diagnosis and treatment. Patients scoring positive using a validated screening questionnaire (either BQ positive, OSA50  $\geq 5$ , or a STOP-BANG cutoff of  $\geq 4$ ) and showing ESS  $\geq 8$  are assigned moderate-to-high risk for OSA and referred directly for in-lab PSG (complex patients) or HSAT (uncomplicated patients) [93]. It is important to point out that patients with negative scores in the proposed questionnaires should not be definitively excluded for OSA [93]. In this situation referring patients to a sleep unit will be required.

Alternatively, other authors proposed a two-step screening strategy involving questionnaires and simplified HSAT in primary care. In a first stage, a battery of sleep questionnaires is applied. Then, abbreviated HSAT approaches can be used in the second stage, e.g., single-channel nasal airflow or pulse oximetry. This two-step approach seems to increase specificity becoming very useful to rule out OSA in primary care while not overstressing sleep units [94, 95].

Application of similar strategies with specific caveats that are exclusively applicable to children are being developed and will hopefully become incorporated into consensus guidelines in the few years to come.

## Impact of COVID-19 Pandemic on Diagnostic Strategy for OSA

The coronavirus disease 2019 (COVID-19) significantly affected healthcare systems worldwide [96, 97]. Social distancing, confinement of population, and additional countermeasures aimed at minimizing virus spread have changed protocols of all medicine disciplines, including sleep laboratories. Particularly, face-to-face in-hospital visits for PSG involved an increased risk for both patients and sleep-related professionals. Moreover, domiciliary approaches also carry infection risk.

Accordingly, during a pandemic, sleep experts strongly recommended to stop performing all kinds of sleep studies, except to hospitalized patients showing high risk of sleep apnea that could worsen their health status [98]. Table 5.9 summarizes

**Table 5.9** Recommendations for in-laboratory sleep assessment during a pandemic

Recommendations
To check body temperature
To ask about novo respiratory symptoms or in contact with a case
To use personal protective equipment (facial mask and gloves)
To use full personal protective equipment when dealing with confirmed cases of infection (protective gown, gloves, facial mask, goggles, and cover boots)
Hand hygiene on arrival and departure and whenever needed

main recommendations when conducting sleep studies in an epidemic context. After the study, the equipment must be disinfected or undergo quarantine if used by infected patients [98]. The epidemic also affects treatment management due to the risk of viral shedding via mask leakage in CPAP devices [99].

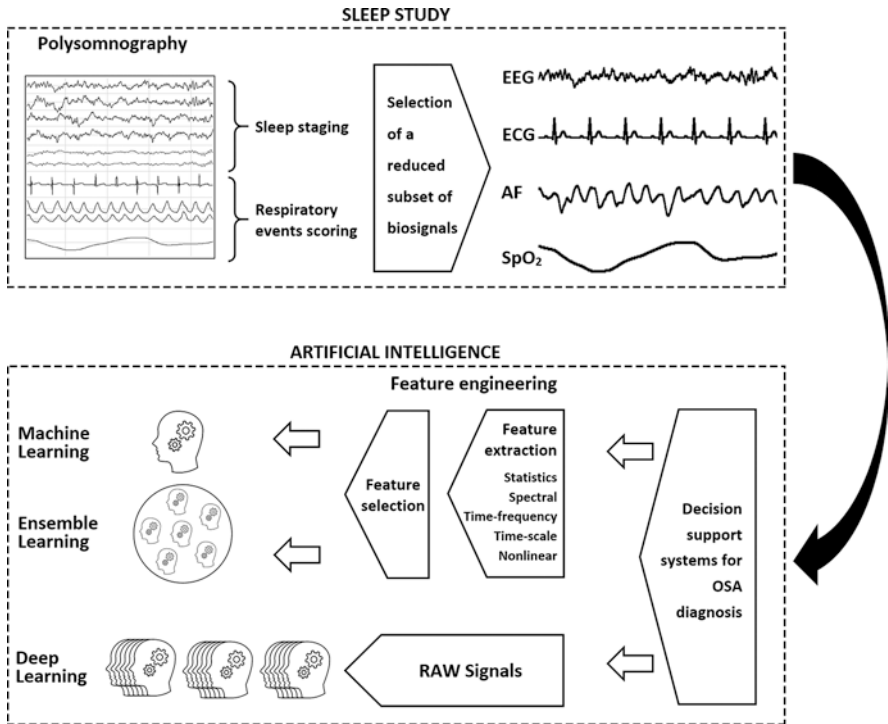
Predicting how this epidemic will finally influence protocols and strategies for management of the disease is difficult. Nevertheless, e-health and HSAT approaches will probably arise as suitable tools to minimize face-to-face diagnosis and follow-up visits [100].

---

### 5.3 Decision Support Systems in OSA Diagnosis

Physicians must deal with several data sources to reach a definitive diagnosis of OSA, including symptoms, anthropometric and clinical variables, and data from biomedical recordings. In this regard, PSG is the main source of information, as it allows physicians to score major electrophysiological and cardiorespiratory events in order to quantify the AHI. Nevertheless, many long-term recordings compose each PSG and many and complex rules must be taken into account to score each type of event. In this context, computer-aided diagnosis systems have been developed as valuable tools that are able to assist physicians in the laborious diagnosis of the disease. Particularly, artificial intelligence has been found to expedite interpretation of physiological signals by decreasing heterogeneity and subjectivity in the PSG scoring task, as well as decreasing the high workload for sleep experts. In fact, the AASM Foundation identified artificial intelligence as a strategic area in which research focused on according to its 2020 Strategic Research Award program.

Figure 5.2 shows how artificial intelligence algorithms are usually used to assist in OSA diagnosis. Regarding conventional machine learning methods, artificial neural networks and support vector machines have been predominantly used due to its nonlinear architecture and generalization ability, able to model real-world complex data with fast and effective processing [101]. In the last several years, ensemble learning techniques, based on the combination of multiple classifiers in order to increase prediction ability, outperformed previous approaches in this context [102].



**Fig. 5.2** Artificial intelligence-based approaches to formulate decision support systems for OSA diagnosis

Deep learning is currently replacing conventional machine learning approaches in several fields of industry and medicine, including sleep research. Deep learning minimizes major shortcomings of classical pattern-recognition algorithms based on feature engineering, which could potentially remove relevant information when composing the initial feature space of input variables [103]. Deep learning models use all the data contained in the signal and compose their own internal features, thus maximizing the diagnostic ability of the signal. Deep neural networks, particularly convolutional neural networks (CNNs), are the most widely used deep learning approach. Similarly, auto-encoders, deep generative models, and recurrent neural networks are also deep learning methods able to characterize biomedical signals [104].

The two main tasks focus the efforts of researchers and developers in the context of decision support systems for OSA management, namely, the development of automated algorithms for sleep staging, aimed at analyzing the macro- and micro-structure of sleep, and automated analysis of cardiorespiratory recordings, in order to obtain simplified and reliable diagnostic tests for OSA. Table 5.10 shows the main tasks involving artificial intelligence in the context of OSA diagnosis.



**Table 5.10** Tasks commonly addressed by means of machine learning and pattern-recognition techniques

Physiological domain	Classification approach	Task	
Sleep	Stage-based	Binary: wake vs. sleep Multi-class: wake vs. N1 to N3 vs. REM	
	Event-based	Arousals, k complexes, spindles	
Respiration	Subject-based	Binary: non-OSA vs. OSA Multi-class: non-OSA vs. mild OSA vs. moderate OSA vs. severe OSA Regression: AHI/RDI/ODI estimation	
		Event-based	Apneic vs. normal breathing Apnea vs. hypopnea events Obstructive vs. central nature

### Automated Sleep Staging from Polysomnography

The interpretation of a PSG is a cumbersome and time-consuming task even for trained experts. Artificial intelligence provides reliable and accurate algorithms to analyze both the macro-structure (sleep/wake time, sleep stages) and the micro-structure (transient events, such as arousals and spindles) of sleep. Particularly, spectral analysis, nonlinear methods, and pattern recognition techniques have been found to provide essential information on electroencephalographic dynamics during sleep and sleep-related breathing disorders [102, 105]. Commercial software by major medical companies in the framework of PSG analysis already implements automated tools for sleep staging. Nevertheless, scoring neuromuscular signals is really challenging for automated algorithms, and accuracy greatly depends on the number of categories (sleep stages) involved in the classification task. Furthermore, performance is also influenced by the type and number of biomedical recordings used (EEG channels and EOG/EMG).

Concerning pattern recognition, according to exhaustive comparisons, a combination of complementary signal-processing approaches including wavelet analysis together with random forest, which is a kind of ensemble learning classifier, is able to reach high efficiency in sleep-staging tasks [106–108]. Recently, a number of studies applied deep learning techniques to accomplish sleep-staging both in healthy subjects and patients with suspected sleep disorders, reporting accuracies ranging from 67.4% to 92.2% [109–117].

### Automated Diagnosis of Sleep Apnea

Decision support systems in the context of OSA diagnosis focus on two main goals: (1) providing a reliable and accurate diagnosis using the least amount of signals, promoting the use of simplified portable monitors able to increase availability and accessibility to sleep-related diagnostic resources, and (2) providing physicians

with automated tools able to decrease the high workload linked with scoring respiratory events.

Regarding abbreviated tests for OSA, the scientific community has focused on the analysis of a reduced subset of cardiorespiratory signals, mainly heart rate variability (HRV) from electrocardiogram (ECG), SpO<sub>2</sub> from oximetry, and airflow (AF). Two approaches are commonly used to characterize changes in these biomedical recordings: time-domain and frequency-domain analyses [118, 119]. In addition, as biological systems have major nonlinear interactions, nonlinear analysis has demonstrated to provide additional and complementary information to conventional linear and frequency-domain methods [120–124]. Similarly, wavelet transform (time-scale analysis) and bispectrum (high-order spectra) have been proposed as reliable alternatives to conventional Fourier analysis in the context of OSA [118, 119, 121].

In order to implement computer-aided diagnosis systems for OSA, binary and multiclass classifiers as well as regression models have been developed (Table 5.10). Classical statistical methods, such as linear (LDA) and quadratic (QDA) discriminant analysis and logistic regression (LR), reached remarkable diagnostic performance in binary classification tasks, whereas more complex machine learning methods including decision trees, neural networks, and support vector machines have demonstrated its usefulness in multiclass and regression problems [101, 118, 119, 125–128]. Recently, ensemble learning and deep learning techniques have been found to outperform conventional machine learning techniques in the framework of OSA diagnosis [104, 129–131].

## Digital Health Technologies in the Management of Sleep Apnea

In the last years, e-Health systems and mobile (m)-health applications through smartphones raised as reliable tools for unattended portable testing and therapy monitoring in the context of OSA management [132, 133]. The increasing recognition of good sleep quality as synonym of health and the need of periodic follow-up in chronic sleep-disordered breathing foster the usefulness of telemedicine in this framework. In this regard, the AASM points out the usefulness of telemedicine for improving accessibility to and availability of sleep experts and sleep-related health-care resources [134].

Regarding high-quality medical applications for clinical practice, e-health/m--health tools mainly focus on long-term therapy tele-monitoring, while remote PSG or alternative simplified sleep studies at home are less frequent [135–137]. On the other hand, the vast majority of smartphone-based applications focus on wellness and lifestyle monitoring for nonspecialized general use, mainly for sleep tracking and sleep quality assessment with a lack of appropriate scientific validation [138–140]. Concerning suitable assessment, the FDA recommends validation against PSG since it is currently the gold standard method for OSA diagnosis. In this regard,

overall, sleep-related parameters provided by mobile Apps correlate poorly with PSG and further improvement is needed [141].

While recent advances focus on simplifying devices to increase portability, accessibility, and comfort, experts point out the lack of direct measures of brain activity, the need for estimating total amount of sleep, and measuring the duration of respiratory events to obtain a reliable and accurate diagnosis of OSA [3].

## **Advantages and Limitations of Artificial Intelligence in the Management of OSA**

Sleep medicine, particularly for sleep-related breathing disorders, can significantly benefit from artificial intelligence and big data techniques due to the huge volume of data involved in the process of diagnosis, including not only PSG but also data from clinical history, anthropometric variables, biomarkers, or genetics, among others. In the last decade, conventional machine learning techniques demonstrated their usefulness in addressing problems related to automated classification of sleep stages, respiratory events, and, overall, sleep apnea severity [142]. In addition, current increased computational capabilities have led novel deep learning algorithms to outperform established limits, reaching correlations above 0.95 in the estimation of the AHI [143] and multi-class kappa above 0.80 in sleep staging [113, 144].

Beyond particular sleep staging and respiratory event scoring tools, artificial intelligence is expected to enhance therapy management and patient outcomes in order to reach the so-called personalized medicine in the context of sleep apnea [142, 145]. In this regard, machine learning has been recently proposed to identify the most appropriate diagnostic pathway for OSA patients. In the work by Stretch et al. [146], a predictive model is trained to decide which patients are referred directly to in-hospital PSG and which ones are more likely to benefit from abbreviated sleep testing at home. Nevertheless, as pointed out in a recent report by the AASM, artificial intelligence is not going to replace sleep experts but to augment efficiency and accurateness of sleep laboratories [147].

On the other hand, common drawbacks of machine learning and artificial intelligence are limited generalizability; output variables and performance metrics difficult to interpret, potentially leading to loss of relevant information; lack of transparency of proprietary algorithms, leading to the so-called black boxes; and subjectivity of standard rules used to label training samples, as automated learning mostly relies on supervised training.

In addition, some major challenges must be still overcome in order to generalize the use of expert systems in clinical practice, such as regulatory laws concerning software certification and logistics linked with computer support, as well as ethical and legal issues [148]. Regarding ethics, it is important to highlight that the clinician is solely responsible for the decisions related to patient diagnosis and treatment.

## References

1. Sil A, Barr G. Assessment of predictive ability of Epworth scoring in screening of patients with sleep apnoea. *J Laryngol Otol*. 2012;126:372–9.
2. Jordan AS, McSharry DG, Malhotra A. Adult obstructive sleep apnoea. *Lancet*. 2014;383:736–47.
3. Mann EA, Nandkumar S, Addy N, Demko BG, Freedman NS, Gillespie MB, et al. Study design considerations for sleep-disordered breathing devices. *J Clin Sleep Med*. 2020;16:441–9.
4. Epstein LJ, Kristo D, Strollo PJ, Friedman N, Malhotra A, Patil SP, et al. Clinical guideline for the evaluation, management and long-term care of obstructive sleep apnea in adults. *J Clin Sleep Med*. 2009;5:263–76.
5. Sharma SK, Katoch VM, Mohan A, Kadiravan T, Elavarasi A, Ragesh R, et al. Consensus and evidence-based Indian initiative on obstructive sleep apnea guidelines 2014 (first edition). *Lung*. 2015;32:422–34.
6. American Academy of Sleep Medicine. International classification of sleep disorders. 3rd ed. Darien: American Academy of Sleep Medicine; 2014.
7. Kaditis AG, Alonso Alvarez ML, Boudewyns A, Alexopoulos EI, Ersu R, Joosten K, et al. Obstructive sleep disordered breathing in 2- to 18-year-old children: diagnosis and management. *Eur Respir J*. 2016;47(1):69–94.
8. Kaditis AG, Alonso Alvarez ML, Boudewyns A, Abel F, Alexopoulos EI, Ersu R, et al. ERS statement on obstructive sleep disordered breathing in 1- to 23-month-old children. *Eur Respir J*. 2017;50(6):1700985.
9. Marcus CL, Brooks LJ, Ward SD, Draper KA, Gozal D, Halbower AC, et al. Diagnosis and management of childhood obstructive sleep apnea syndrome. *Pediatrics*. 2012;130(3):e714–55.
10. Kapur VK, Auckley DH, Chowdhuri S, Kuhlmann DC, Mehra R, Ramar K, et al. Clinical practice guideline for diagnostic testing for adult obstructive sleep apnea: an American Academy of Sleep Medicine clinical practice guideline. *J Clin Sleep Med*. 2017;13:479–504.
11. Borsini E, Blanco M, Schonfeld S, Ernst G, Salvado A. Performance of Epworth Sleepiness Scale and tiredness symptom used with simplified diagnostic tests for the identification of sleep apnea. *Sleep Sci*. 2019;12:287–94.
12. Chiu HY, Chen PY, Chuang LP, Chen NH, Tu YK, Hsieh YJ, et al. Diagnostic accuracy of the Berlin questionnaire, STOP-BANG, STOP, and Epworth sleepiness scale in detecting obstructive sleep apnea: a bivariate meta-analysis. *Sleep Med Rev*. 2017;36:57–70.
13. Ahmadi N, Chung SA, Gibbs A, Shapiro CM. The Berlin questionnaire for sleep apnea in a sleep clinic population: relationship to polysomnographic measurement of respiratory disturbance. *Sleep Breath*. 2008;12:39–45.
14. Chai-Coetzer CL, Antic NA, Rowland LS, Catcheside PG, Esterman A, Reed RL, et al. A simplified model of screening questionnaire and home monitoring for obstructive sleep apnoea in primary care. *Thorax*. 2011;66:213–9. <https://doi.org/10.1136/thx.2010.152801>.
15. Chung F, Abdullah HR, Liao P. STOP-Bang questionnaire: a practical approach to screen for obstructive sleep apnea. *Chest*. 2016;149:631–8.
16. Gasparini G, Vicini C, De Benedetto M, Salamanca F, Sorrenti G, Romandini M, et al. Diagnostic accuracy of obstructive airway adult test for diagnosis of obstructive sleep apnea. *Biomed Res Int*. 2015;2015:915185.
17. Tietjens JR, Claman D, Kezirian EJ, De Marco T, Mirzayan A, Sadroonri B, et al. Obstructive sleep apnea in cardiovascular disease: a review of the literature and proposed multidisciplinary clinical management strategy. *J Am Heart Assoc*. 2019;8:e010440.
18. Bibbins-Domingo K, Grossman DC, Curry SJ, Davidson KW, Epling JW Jr, García FAR, et al. Screening for obstructive sleep apnea in adults: US Preventive Services Task Force recommendation statement. *JAMA*. 2017;317:407–14.
19. Duarte RLM, Magalhães-da-Silveira FJ, Gozal D. Sex-dependent GOAL screening performance in adults at risk for obstructive sleep apnea. *Pulmonology*. 2022. <https://doi.org/10.1016/j.pulmoe.2022.01.004>. PMID: 35151621.

20. Duarte RLM, Magalhães-da-Silveira FJ, Gozal D. Prediction of obstructive sleep apnea using GOAL questionnaire in adults with or without excessive daytime sleepiness: a cross-sectional study. *Sleep Health*. 2021;7(2):212–8.
21. Duarte RLM, Silveira FJMD, Sá TSOE, Rabahi MF, Mello FCQ, Gozal D. Using the no apnea score to screen for obstructive sleep apnea in adults referred to a sleep laboratory: comparative study of the performance of the instrument by gender. *J Bras Pneumol*. 2020;46(5):e20190297.
22. Duarte RLM, Magalhães-da-Silveira FJ, Gozal D. Validation of the GOAL Questionnaire as an Obstructive Sleep Apnea screening instrument in bariatric surgery candidates: a Brazilian single-center study. *Obes Surg*. 2020;30(12):4802–9.
23. Duarte RLM, Magalhães-da-Silveira FJ, Oliveira-e-Sá TS, Silva JA, Mello FCQ, Gozal D. Obstructive sleep apnea screening with a 4-item instrument, named GOAL questionnaire: development, validation and comparative study with no-apnea, STOP-Bang, and NoSAS. *Nat Sci Sleep*. 2020;12:57–67.
24. Duarte RLM, Mello FCQ, Magalhães-da-Silveira FJ, Oliveira-E-Sá TS, Rabahi MF, Gozal D. Comparative performance of screening instruments for obstructive sleep apnea in morbidly obese patients referred to a sleep laboratory: a prospective cross-sectional study. *Sleep Breath*. 2019;23(4):1123–32.
25. Duarte RLM, Magalhães-da-Silveira FJ, Oliveira-E-Sá TS, Rabahi MF, Mello FCQ, Gozal D. Predicting obstructive sleep apnea in patients with insomnia: a comparative study with four screening instruments. *Lung*. 2019;197(4):451–8.
26. Duarte RLM, Rabahi MF, Magalhães-da-Silveira FJ, de Oliveira-E-Sá TS, Mello FCQ, Gozal D. Simplifying the screening of obstructive sleep apnea with a 2-item model, no-apnea: a cross-sectional study. *J Clin Sleep Med*. 2018;14(7):1097–107.
27. Miller NJ, Kupzik KA, Zimmerman L, Pozehl B, Schulz P, Romberger D, et al. Comparisons of measures used to screen for obstructive sleep apnea in patients referred to a sleep clinic. *Sleep Med*. 2018;51:15–21.
28. Tanphaichitr A, Chuenchod P, Ungkanont K, Banhiran W, Vathanophas V, Gozal D. Validity and reliability of the Thai version of the pediatric obstructive sleep apnea screening tool. *Pediatr Pulmonol*. 2021;56(9):2979–86.
29. Pires PJS, Mattiello R, Lumertz MS, Morsch TP, Fagondes SC, Nunes ML, Gozal D, Stein RT. Validation of the Brazilian version of the pediatric obstructive sleep apnea screening tool questionnaire. *J Pediatr*. 2019;95(2):231–7.
30. Nguyễn XL, Lévy P, Beydon N, Gozal D, Fleury B. Performance characteristics of the French version of the severity hierarchy score for paediatric sleep apnoea screening in clinical settings. *Sleep Med*. 2017;30:24–8.
31. Kadmon G, Shapiro CM, Chung SA, Gozal D. Validation of a pediatric obstructive sleep apnea screening tool. *Int J Pediatr Otorhinolaryngol*. 2013;77(9):1461–4.
32. Erichsen D, Godoy C, Gränse F, Axelsson J, Rubin D, Gozal D. Screening for sleep disorders in pediatric primary care: are we there yet? *Clin Pediatr*. 2012;51(12):1125–9.
33. Spruyt K, Gozal D. Screening of pediatric sleep-disordered breathing: a proposed unbiased discriminative set of questions using clinical severity scales. *Chest*. 2012;142(6):1508–15.
34. Laratta CR, Ayas NT, Povitz M, Pendharkar SR. Diagnosis and treatment of obstructive sleep apnea in adults. *CMAJ*. 2017;189:E1481–8.
35. Berry RB, Brooks R, Gamaldo CE, Sm H, Lloyd RM, Marcus CL, et al. The AASM manual for the scoring of sleep and associated events: rules, terminology and technical specifications, version 2.6.0. Darien: American Academy of Sleep Medicine; 2020.
36. Scapuccin M, Schneider L, Rashid N, Zaghi S, Rosa T, Tsou Y-A, et al. Integrating the divided nasal cannula into routine polysomnography to assess nasal cycle: feasibility and effect on outcomes. *J Clin Sleep Med*. 2018;14:641–50.
37. Peppard PE, Hagen EW. Reply to Holley and Phillips: the next 25 years of obstructive sleep apnea epidemiology - don't keep repeating past mistakes. *Am J Respir Crit Care Med*. 2018;198:410–1.

38. Hunter SJ, Gozal D, Smith DL, Philby MF, Kaylegian J, Kheirandish-Gozal L. Effect of sleep-disordered breathing severity on cognitive performance measures in a large community cohort of young school-aged children. *Am J Respir Crit Care Med.* 2016;194(6):739–47.
39. Smith DL, Gozal D, Hunter SJ, Kheirandish-Gozal L. Frequency of snoring, rather than apnea-hypopnea index, predicts both cognitive and behavioral problems in young children. *Sleep Med.* 2017;34:170–8.
40. Collop NA, Anderson WM, Boehlecke B, Claman D, Goldberg R, Gottlieb DJ, et al. Portable monitoring task force of the American academy of sleep medicine clinical guidelines for the use of unattended portable monitors in the diagnosis of obstructive sleep apnea in adult patients. Portable monitoring task force of the American Academy of Sleep Medicine. *J Clin Sleep Med.* 2007;3:737–47.
41. Fietze I, Laharnar N, Bargiotas P, Basoglu OK, Dogas Z, Drummond M, et al. Management of obstructive sleep apnea in Europe - a 10-year follow-up. *Sleep Med.* 2022;97:64–72. <https://doi.org/10.1016/j.sleep.2022.06.001>.
42. Stewart SA, Skomro R, Reid J, Penz E, Fenton M, Gjevje J, et al. Improvement in obstructive sleep apnea diagnosis and management wait times: a retrospective analysis of a home management pathway for obstructive sleep apnea. *Can Respir J.* 2015;22:167–70.
43. Bianchi MT, Goparaju B. Potential underestimation of sleep apnea severity by at-home kits: rescoring in-laboratory polysomnography without sleep staging. *J Clin Sleep Med.* 2017;13:551–5.
44. Tan HL, Kheirandish-Gozal L, Gozal D. Pediatric home sleep apnea testing: slowly getting there! *Chest.* 2015;148(6):1382–95.
45. Tan HL, Gozal D, Ramirez HM, Bandla HP, Kheirandish-Gozal L. Overnight polysomnography versus respiratory polygraphy in the diagnosis of pediatric obstructive sleep apnea. *Sleep.* 2014;37(2):255–60.
46. Rosen CL, Auckley D, Benca R, Foldvary-Schaefer N, Iber C, Kapur V, et al. A multisite randomized trial of portable sleep studies and positive airway pressure autotitration versus laboratory-based polysomnography for the diagnosis and treatment of obstructive sleep apnea: the HomePAP study. *Sleep.* 2012;35:757–67.
47. Pietzsch JB, Garner A, Cipriano LE, Linehan JH. An integrated health-economic analysis of diagnostic and therapeutic strategies in the treatment of moderate-to-severe obstructive sleep apnea. *Sleep.* 2011;34:695–709.
48. Rundo JV, Downey R. Clinical neurophysiology: basis and technical aspects. In: *Handbook of clinical neurology*, vol. 160. Amsterdam: Elsevier; 2019.
49. Douglas JA, Chai-Coetzer CL, McEvoy D, Naughton MT, Neill AM, Rochford P, et al. Guidelines for sleep studies in adults – a position statement of the Australasian Sleep Association. *Sleep Med.* 2017;36:S2–22. <https://doi.org/10.1016/j.sleep.2017.03.019>.
50. Alonso-Álvarez ML, Terán-Santos J, Ordax Carbajo E, Cordero-Guevara JA, Navazo-Egüia AI, Kheirandish-Gozal L, Gozal D. Reliability of home respiratory polygraphy for the diagnosis of sleep apnea in children. *Chest.* 2015;147(4):1020–8.
51. Masa JF, Corral J, Pereira R, Duran-Cantolla J, Cabello M, Hernández-Blasco L, et al. Effectiveness of home respiratory polygraphy for the diagnosis of sleep apnoea and hypopnoea syndrome. *Thorax.* 2011;66:567–73.
52. Woods CE, Usher KJ, Jersmann H, Maguire GP. Sleep disordered breathing and polysomnography in Australia: trends in provision from 2005 to 2012 and the impact of home-based diagnosis. *J Clin Sleep Med.* 2014;10:767–72.
53. El Shayeb M, Topfer L-A, Stafinski T, Pawluk L, Menon D. Diagnostic accuracy of level 3 portable sleep tests versus level I polysomnography for sleep-disordered breathing: a systematic review and meta-analysis. *CMAJ.* 2014;186:E25–51.
54. Kim RD, Kapur VK, Redline-Bruch J, Rueschman M, Auckley DH, Benca RM, et al. An economic evaluation of home versus laboratory-based diagnosis of obstructive sleep apnea. *Sleep.* 2015;38:1027–37.
55. Stewart SA, Penz E, Fenton M, Skomro R. Investigating cost implications of incorporating level iii at-home testing into a polysomnography based sleep medicine program using administrative data. *Can Respir J.* 2017;2017:8939461.

56. Lipatov K, Hayek A, Ghamande S, Boethel C, Chen W, Jones S. Predictors of obstructive sleep apnea on a home sleep apnea test after a negative attended polysomnography. *Clin Sleep Med*. 2018;14:1889–94.
57. Kapur VK, Johnston JC, Rueschman M, Bakker JP, Donovan LM, Hanson M, et al. Patient satisfaction with sleep study experience: findings from the Sleep Apnea Patient-Centered Outcomes Network. *Sleep*. 2018;41:93.
58. Andrade L, Paiva T. Ambulatory versus laboratory polysomnography in obstructive sleep apnea: comparative assessment of quality, clinical efficacy, treatment compliance, and quality of life. *J Clin Sleep Med*. 2018;14:1323–31.
59. Gozal D, Kheirandish-Gozal L, Kaditis AG. Home sleep testing for the diagnosis of pediatric obstructive sleep apnea: the times they are a changing...! *Curr Opin Pulm Med*. 2015;21(6):563–8.
60. Kaditis A, Kheirandish-Gozal L, Gozal D. Algorithm for the diagnosis and treatment of pediatric OSA: a proposal of two pediatric sleep centers. *Sleep Med*. 2012;13(3):217–27.
61. Rosen IM, Kirsch DB, Carden KA, Malhotra RK, Ramar K, Aurora RN, et al. Clinical use of a home sleep apnea test: an updated American Academy of Sleep Medicine position statement. *J Clin Sleep Med*. 2018;14(12):2075–7.
62. Dawson A, Loving RT, Gordon RM, Abel SL, Loewy D, Kripke DF, et al. Type III home sleep testing versus pulse oximetry: is the respiratory disturbance index better than the oxygen desaturation index to predict the apnoea-hypopnoea index measured during laboratory polysomnography? *BMJ Open*. 2015;5:e007956.
63. Maricoto T, Silva EAR, Damião P, Bastos JM. The OXIMAPA study: hypertension control by ABPM and association with sleep apnea syndrome by pulse oximetry. *Acta Medica Port*. 2017;30:93–9.
64. Ward NR, Cowie MR, Rosen SD, Roldao V, De Villa M. Utility of overnight pulse oximetry and heart rate variability analysis to screen for sleep-disordered breathing in chronic heart failure. *Thorax*. 2012;67:100–5.
65. Aaronson JA, Van Bezeij T, Van den Aardweg JG, Van Bennekom CAM, Hofman WF. Diagnostic accuracy of nocturnal oximetry for detection of sleep apnea syndrome in stroke rehabilitation. *Stroke*. 2012;43:2491–3.
66. Oliveira MG, Nery LE, Santos-Silva R, Sartori DE, Alonso FF, Togeiro SM, et al. Is portable monitoring accurate in the diagnosis of obstructive sleep apnea syndrome in chronic pulmonary obstructive disease? *Sleep Med*. 2012;13:1033–8.
67. Andrés-Blanco MA, Álvarez D, Crespo A, Arroyo A, Cerezo-Hernández A, Gutiérrez-Tobal GC, et al. Assessment of automated analysis of portable oximetry as a screening test for moderate-to-severe sleep apnea in patients with chronic obstructive pulmonary disease. *PLoS One*. 2017;12:e0188094.
68. Malbois M, Giusti V, Suter M, Pellaton C, Vodoz J-F, Heinzer R. Oximetry alone versus portable polygraphy for sleep apnea screening before bariatric surgery. *Obes Surg*. 2010;20:326–31.
69. Chung F, Liao P, Elsaid H, Islam S, Shapiro CM, Sun Y. Oxygen desaturation index from nocturnal oximetry: a sensitive and specific tool to detect sleep-disordered breathing in surgical patients. *Anesth Analg*. 2012;114:993–1000.
70. Mazière S, Pepin JL, Siyanko N, Bioteau C, Launois S, Tamisier R, et al. Usefulness of oximetry for sleep apnea in frail hospitalized elderly. *J Am Med Dir Assoc*. 2014;15:447.
71. Linz D, Colling S, Nußstein W, Debl K, Hohl M, Fellner C, et al. Nocturnal hypoxemic burden is associated with epicardial fat volume in patients with acute myocardial infarction. *Sleep Breath*. 2018;22:703–11.
72. Seijo LM, Pérez-Warnisher MT, Giraldo-Cadavid LF, Oliveros H, Cabezas E, Troncoso MF, et al. Obstructive sleep apnea and nocturnal hypoxemia are associated with an increased risk of lung cancer. *Sleep Med*. 2019;63:41–5.
73. Azarbarzin A, Sands SA, Stone KL, Taranto-Montemurro L, Messineo L, Terrill PI, et al. The hypoxic burden of sleep apnoea predicts cardiovascular disease-related mortality: the osteoporotic fractures in men study and the Sleep Heart Health Study. *Eur Heart J*. 2019;40:1149–57.

74. Kulkas A, Tiitonen P, Eskola K, Julkunen P, Mervaala E, Töyräs J. Novel parameters for evaluating severity of sleep disordered breathing and for supporting diagnosis of sleep apnea-hypopnea syndrome. *J Med Eng Technol*. 2013;37:135–43.
75. Villa MP, Pietropaoli N, Supino MC, Vitelli O, Rabasco J, Evangelisti M, et al. Diagnosis of pediatric obstructive sleep apnea syndrome in settings with limited resources. *JAMA Otolaryngol Head Neck Surg*. 2015;141(11):990–6.
76. 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.
77. Polytarchou A, Ohler A, Moudaki A, Koltsida G, Kanaka-Gantenbein C, Kheirandish-Gozal L, et al. Nocturnal oximetry parameters as predictors of sleep apnea severity in resource-limited settings. *J Sleep Res*. 2022. <https://doi.org/10.1111/jsr.13638>. PMID: 35624085.
78. De Luca CG, Pachêco-Pereira C, Aydinoz S, Major PW, Flores-Mir C, Gozal D. Biomarkers associated with obstructive sleep apnea: a scoping review. *Sleep Med Rev*. 2015;23:28–45.
79. Alonso-Álvarez ML, Terán-Santos J, Gonzalez Martinez M, Cordero-Guevara JA, Jurado-Luque MJ, Corral-Peñafiel J, et al. Metabolic biomarkers in community obese children: effect of obstructive sleep apnea and its treatment. *Sleep Med*. 2017;37:1–9.
80. Elsharkawi I, Gozal D, Macklin EA, Voelz L, Weintraub G, Skotko BG. Urinary biomarkers and obstructive sleep apnea in patients with Down syndrome. *Sleep Med*. 2017;34:84–9.
81. Kheirandish-Gozal L, Gozal D. Pediatric OSA syndrome morbidity biomarkers: the hunt is finally on! *Chest*. 2017;151(2):500–6.
82. Bhattacharjee R, Kheirandish-Gozal L, Kaditis AG, Verhulst SL, Gozal D. C-reactive protein as a potential biomarker of residual obstructive sleep apnea following adenotonsillectomy in children. *Sleep*. 2016;39(2):283–91.
83. Becker L, Kheirandish-Gozal L, Peris E, Schoenfelt KQ, Gozal D. Contextualised urinary biomarker analysis facilitates diagnosis of paediatric obstructive sleep apnoea. *Sleep Med*. 2014;15(5):541–9.
84. Gozal D. Serum, urine, and breath-related biomarkers in the diagnosis of obstructive sleep apnea in children: is it for real? *Curr Opin Pulm Med*. 2012;18(6):561–7.
85. Gozal D, Jortani S, Snow AB, Kheirandish-Gozal L, Bhattacharjee R, Kim J, Capdevila OS. Two-dimensional differential in-gel electrophoresis proteomic approaches reveal urine candidate biomarkers in pediatric obstructive sleep apnea. *Am J Respir Crit Care Med*. 2009;180(12):1253–61.
86. Fleming WE, Holty J-EC, Bogan RK, Hwang D, Ferouz-Colborn AS, Budhiraja R, et al. Use of blood biomarkers to screen for obstructive sleep apnea. *Nat Sci Sleep*. 2018;10:159–67.
87. Sánchez-de-la-Torre M, Khalyfa A, Sánchez-de-la-Torre A, Martínez-Alonso M, Martínez-García MÁ, Barceló A, et al. Precision medicine in patients with resistant hypertension and obstructive sleep apnea: blood pressure response to continuous positive airway pressure treatment. *J Am Coll Cardiol*. 2015;66(9):1023–32.
88. Al-Mughales J, Wali SO, Manzar MD, Alhejaili F, Gozal D. Pro-inflammatory markers in patients with obstructive sleep apnea and the effect of continuous positive airway pressure therapy. *Sleep Sci*. 2022;15(1):20–7.
89. Wali SO, Al-Mughales J, Alhejaili F, Manzar MD, Alsallum F, Almojaddidi H, et al. The utility of proinflammatory markers in patients with obstructive sleep apnea. *Sleep Breath*. 2021;25(2):545–53. <https://doi.org/10.1007/s11325-020-02149-3>. Epub 2020 Jul 23. Erratum in: *Sleep Breath*. 2022 Mar 28; PMID: 32705528.
90. Khalyfa A, Gozal D, Chan WC, Andrade J, Prasad B. Circulating plasma exosomes in obstructive sleep apnoea and reverse dipping blood pressure. *Eur Respir J*. 2020;55(1):1901072.
91. De Luca CG, Pachêco-Pereira C, Aydinoz S, Major PW, Flores-Mir C, Gozal D. Diagnostic capability of biological markers in assessment of obstructive sleep apnea: a systematic review and meta-analysis. *J Clin Sleep Med*. 2015;11:27–36.
92. Kuna ST. Diagnosis and management of patients with obstructive sleep apnea in primary care ready or not? *Am J Respir Crit Care Med*. 2018;198:557–8.
93. Hamilton GS, Chai-Coetzer CL. Update on the assessment and investigation of adult obstructive sleep apnoea. *Austr J Gen Pract*. 2019;48:176–81.



94. Eijsvogel MM, Wiegersma S, Randerath W, Verbraecken J, Wegter-Hilbers E, Van der Palen J. Obstructive sleep apnea syndrome in company workers: development of a two-step screening strategy with a new questionnaire. *J Clin Sleep Med.* 2016;12:555–64.
95. Donovan LM, Shah A, Chai-Coetzer CL, Barbé F, Ayas NT, Kapur VK. Redesigning care for OSA. *Chest.* 2020;157:966–76.
96. Zhu N, Zhang D, Wang W, Li X, Yang B, Song J. A novel coronavirus from patients with pneumonia in China, 2019. *N Engl J Med.* 2020;382:727–33.
97. Chan JF, Yuan S, Kok KH, To KK, Chu H, Yang J. A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of family cluster. *Lancet.* 2020;385:514–23.
98. Drummond M. Sleep labs, lung function tests and COVID-19 pandemic – only emergencies allowed! *Pulmonology.* 2020;26(4):244–5.
99. Kryger M, Thomas R. Home PAP devices in COVID-19 infected patients. *J Clin Sleep Med.* 2020;16(7):1217–9.
100. Lurie N, Carr BG. The role of telehealth in the medical response to disasters. *JAMA Intern Med.* 2018;178:745–6.
101. Álvarez D, Cerezo-Hernández A, López-Muñiz G, Álvaro-De Castro TM, Ruiz-Albi T, Hornero R, et al. Usefulness of artificial neural networks in the diagnosis and treatment of sleep apnea-hypopnea syndrome. In: Vats MG, editor. *Sleep apnea - recent updates.* Rijeka: InTech; 2017.
102. Fiorillo L, Puiatti A, Papandrea M, Ratti P-L, Favaro P, Roth C, et al. Automated sleep scoring: a review of the latest approaches. *Sleep Med Rev.* 2019;48:101204.
103. LeCun Y, Bengio Y, Hinton G. Deep learning. *Nature.* 2015;521:436–44. <https://doi.org/10.1038/nature14539>.
104. Faust O, Hagiwara Y, Hong TJ, Lih OS, Acharya UR. Deep learning for healthcare applications based on physiological signals: a review. *Comput Methods Progr Biomed.* 2018;161:1–13. <https://doi.org/10.1016/j.cmpb.2018.04.005>.
105. Acharya UR, Bhat S, Faust O, Adeli H, Chua EC-P, Lim WJE, et al. Nonlinear dynamics measures for automated EEG-based sleep stage detection. *Eur Neurol.* 2015;74:268–87.
106. Sen B, Peker M, Çavusoglu A, Çelebi FV. A comparative study on classification of sleep stage based on EEG signals using feature selection and classification algorithms. *J Med Syst.* 2014;38:18.
107. Aboalayon K, Faezipour M, Almuhammadi W, Moslehpour S. Sleep stage classification using EEG signal analysis: a comprehensive survey and new investigation. *Entropy.* 2016; 18:272.
108. Boostani R, Karimzadeh F, Nami M. A comparative review on sleep stage classification methods in patients and healthy individuals. *Comput Methods Prog Biomed.* 2017;140:77–91.
109. Långkvist M, Karlsson L, Loutfi A. Sleep stage classification using unsupervised feature learning. *Adv Artif Neural Syst.* 2012;2012:107046. <https://doi.org/10.1155/2012/107046>.
110. Supratak A, Dong H, Wu C, Guo Y. DeepSleepNet: a model for automatic sleep stage scoring based on raw single-channel EEG. *IEEE Trans Neural Syst Rehabil Eng.* 2017;25:1998–2008.
111. Cui Z, Zheng X, Shao X, Cui L. Automatic sleep stage classification based on convolutional neural network and fine-grained segments. *Complexity.* 2018;2018:9248410.
112. Malafeev A, Laptev D, Bauer S, Omlin X, Wierzbicka A, Wichniak A, et al. Automatic human sleep stage scoring using deep neural networks. *Front Neurosci.* 2018;12:781.
113. Patanaik A, Ong JL, Gooley JJ, Ancoli-Israel S, Chee MW. An end-to-end framework for real-time automatic sleep stage classification. *Sleep.* 2018;41:1–18.
114. Zhang J, Wu Y. Complex-valued unsupervised convolutional neural networks for sleep stage classification. *Comput Methods Progr Biomed.* 2018;164:181–91.
115. Phan H, Andreotti F, Cooray N, Chn OY, De Vos M. SeqSleepNet: end-to-end hierarchical recurrent neural network for sequence-to-sequence automatic sleep staging. *IEEE Trans Neural Syst Rehabil Eng.* 2019;27:400–10.
116. Yildirim O, Baloglu UB, Acharya UR. A deep learning model for automated sleep stages classification using PSG signals. *Int J Environ Res Public Health.* 2019;16:599.

117. Zhang L, Fabbri D, Upender R, Kent D. Automated sleep stage scoring of the Sleep Heart Health Study using deep neural networks. *Sleep*. 2019;42:159.
118. Roebuck A, Monasterio V, Gederi E, Osipov M, Behar J, Malhotra A, et al. A review of signals used in sleep analysis. *Physiol Meas*. 2014;35:1–57.
119. Shokouejad M, Fernandez C, Carroll E, Wang F, Levin J, Rusk S, et al. Sleep apnea: a review of diagnostic sensors, algorithms, and therapies. *Physiol Meas*. 2017;38:204–52.
120. Penzel T, Kantelhardt JW, Grote L, Peter J-H, Bunde A. Comparison of detrended fluctuation analysis and spectral analysis of heart rate variability in sleep and sleep apnea. *IEEE Trans Biomed Eng*. 2003;50:1143–51.
121. Mendez MO, Corthout J, Van Huffel S, Matteucci M, Penzel T, Cerutti S, et al. Automatic screening of obstructive sleep apnea from the ECG based on empirical mode decomposition and wavelet analysis. *Physiol Meas*. 2010;31:273–89.
122. Álvarez D, Hornero R, Abásolo D, del Campo F, Zamarrón C. Nonlinear characteristics of blood oxygen saturation from nocturnal oximetry for obstructive sleep apnoea detection. *Physiol Meas*. 2006;27:399–412.
123. Álvarez D, Hornero R, Marcos JV, del Campo F. Feature selection from nocturnal oximetry using genetic algorithms to assist in obstructive sleep apnoea diagnosis. *Med Eng Phys*. 2012;34:104–57.
124. Gutiérrez-Tobal GC, Álvarez D, Gomez-Pilar J, Del Campo F, Hornero R. Assessment of time and frequency domain entropies to detect sleep apnoea in heart rate variability recordings from men and women. *Entropy*. 2015;17:123–41.
125. Álvarez D, Hornero R, Marcos JV, Wessel N, Penzel T, Glos M, et al. Assessment of feature selection and classification approaches to enhance information from overnight oximetry in the context of apnea diagnosis. *Int J Neural Syst*. 2013;23:1350020.
126. Gutiérrez-Tobal GC, Álvarez D, Marcos JV, Del Campo F, Hornero R. Pattern recognition in airflow recordings to assist in the sleep apnoea–hypopnoea syndrome diagnosis. *Med Biol Eng Comput*. 2013;51:1367–80.
127. Del Campo F, Crespo A, Cerezo-Hernández A, Gutiérrez-Tobal GC, Hornero R, Álvarez D. Oximetry use in obstructive sleep apnea. *Expert Rev Respir Med*. 2018;12:665–81.
128. Álvarez D, Cerezo-Hernández A, Crespo A, Gutiérrez-Tobal GC, Vaquerizo-Villar F, Barroso-García V, et al. A machine learning-based test for adult sleep apnoea screening at home using oximetry and airflow. *Sci Rep*. 2020;10:5332. <https://doi.org/10.1038/s41598-020-62223-4>.
129. Gutiérrez-Tobal GC, Álvarez D, Del Campo F, Hornero R. Utility of AdaBoost to detect sleep apnea-hypopnea syndrome from single-channel airflow. *IEEE Trans Biomed Eng*. 2016;63:636–46.
130. Mostafa SS, Mendonça F, Ravelo-García AG, Morgado-Dias F. A systematic review of detecting sleep apnea using deep learning. *Sensors*. 2019;19:4934.
131. Gutiérrez-Tobal GC, Álvarez D, Crespo A, del Campo F, Hornero R. Evaluation of machine-learning approaches to estimate sleep apnea severity from at-home oximetry recordings. *IEEE J Biomed Health Inf*. 2019;23:882–92.
132. Shelgikar AV, Anderson PF, Stephens MR. Sleep tracking, wearable technology, and opportunities for research and clinical care. *Chest*. 2016;150:732–43.
133. Camacho M, Roberson M, Abdullatif J, et al. Smartphone apps for snoring. *J Laryngol Otol*. 2015;129:974–9.
134. Singh J, Badr MS, Diebert W, Epstein L, Hwang D, Karres V, et al. American Academy of Sleep Medicine (AASM) position paper for the use of telemedicine for the diagnosis and treatment of sleep disorders. *J Clin Sleep Med*. 2015;11:1187–98.
135. Verbraecken J. Telemedicine applications in sleep disordered breathing. Thinking out of the box. *Sleep Med Clin*. 2016;11:445–59.
136. Behar J, Roebuck A, Shahid M, Daly J, Hallack A, Palmius N, et al. SleepAp: an automated obstructive sleep apnoea screening application for smartphones. *IEEE J Biomed Health Inf*. 2015;19:325–31.

137. Garde A, Dehkordi P, Karlen W, Wensley D, Ansermino JM, Dumont GA. Development of a screening tool for sleep disordered breathing in children using the Phone Oximeter™. *PLoS ONE*. 2014;9:e112959.
138. Behar J, Roebuck A, Domingos JS, Geder E, Clifford GD. A review of current sleep screening applications for smartphones. *Physiol Meas*. 2013;34:29–6.
139. Ko P-RT, Kientz JA, Choe EK, Kay M, Landis CA, Watson NF. Consumer sleep technologies: a review of the landscape. *Clin. Sleep Med*. 2015;11:1455–61.
140. Penzel T, Schöbel C, Fietze I. New technology to assess sleep apnea: wearables, smartphones, and accessories. *F1000 Res*. 2018;7:413.
141. Bhat S, Ferraris A, Gupta D, Mozafarian M, DeBari VA, Gushway-Henry N, et al. Is there a clinical role for smartphone sleep apps? Comparison of sleep cycle detection by a smartphone application to polysomnography. *J Clin Sleep Med*. 2015;11:709–15.
142. Mazzotti DR, Lim DC, Sutherland K, Bittencourt L, Mindel JW, Magalang U, et al. Opportunities for utilizing polysomnography signals to personalize obstructive sleep apnea subtypes and severity. *Physiol Meas*. 2018;39:09TR01.
143. Nikkonen S, Afara IO, Leppänen T, Töyräs J. Artificial neural network analysis of the oxygen saturation signal enables accurate diagnostics of sleep apnea. *Sci Rep*. 2019;9:13200.
144. Biswal S, Sun H, Goparaju B, Westover MB, Sun J, Bianchi MT. Expert-level sleep scoring with deep neural networks. *J Am Med Inform Assoc*. 2018;25:1643–50.
145. Martínez-García MA, Campos-Rodríguez F, Barbé F, Gozal D, Agustí A. Precision medicine in obstructive sleep apnea. *Lancet Respir Med*. 2019;7:456–64.
146. Stretch R, Ryden A, Fung CH, Martires J, Liu S, Balasubramanian V, et al. Predicting nondiagnostic home sleep apnea tests using machine learning. *J Clin Sleep Med*. 2019;15:1599–608.
147. Goldstein CA, Berry RB, Kent DT, Kristo DA, Seixas AA, Redline S, et al. Artificial intelligence in sleep medicine: an American Academy of Sleep Medicine position statement. *J Clin Sleep Med*. 2020;16:605–7.
148. Goldstein CA, Berry RB, Kent DT, Kristo DA, Seixas AA, Redline S, et al. Artificial intelligence in sleep medicine: background and implications for clinicians. *J Clin Sleep Med*. 2020;16:609–18.