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REVIEW

Enhancing artificial intelligence-driven sleep apnea diagnosis: The critical importance of input signal proficiency with a focus on mandibular jaw movements

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Abstract

Purpose: This review aims to highlight the pivotal role of the mandibular jaw movement (MJM) signal in advancing artificial intelligence (AI)-powered technologies for diagnosing obstructive sleep apnea (OSA).

Methods: A scoping review was conducted to evaluate various aspects of the MJM signal and their contribution to improving signal proficiency for users.

Results: The comprehensive literature analysis is structured into four key sections, each addressing factors essential to signal proficiency. These factors include (1) the comprehensiveness of research, development, and application of MJM-based technology; (2) the physiological significance of the MJM signal for various clinical tasks; (3) the technical transparency; and (4) the interpretability of the MJM signal. Comparisons with the photoplethysmography (PPG) signal are made where applicable.

Conclusions: Proficiency in biosignal interpretation is essential for the success of AI-driven diagnostic tools and for maximizing the clinical benefits through enhanced physiological insight. Through rigorous research ensuring an enhanced understanding of the signal and its extensive validation, the MJM signal sets a new benchmark for the development of AI-driven diagnostic solutions in OSA diagnosis.

KEYWORDS
artificial intelligence, biosignal literacy, mandibular jaw movements, sleep apnea, technical transparency

Sleep medicine has long faced challenges in balancing the use of conventional polysomnography (PSG), still considered the gold standard for diagnosing obstructive sleep apnea (OSA) but associated with significant drawbacks, with the need to address large-scale epidemiological demands for diagnosing and managing OSA.[1]

In recent years, novel artificial intelligence (AI)-based analytic methods for sleep testing have gained increasing attention. Over the past decade, advancements in biosensor technology,[2] machine learning methodology,[3,4] and new physiological signals[5] have driven the development of innovative AI-powered sleep testing devices. Furthermore, improvements in miniaturization, signal processing, and data science have enabled the creation of a new generation of multisensory sleep diagnostic tools.[6,7]

However, this fast-paced innovation has introduced new challenges, such as fragmented knowledge, limited technical transparency, and the tendency to neglect or oversimplify essential steps in research and development. These challenges can hinder the effective adoption of AI-based solutions by healthcare professionals and impede their engagement with new biosignal technologies.

The American Academy of Sleep Medicine (AASM) recently underscored that AI should support, not replace, clinical expertise in sleep medicine.[8] Technology developers are urged to assist physicians in evaluating the performance of new AI-based technologies, including raw data review. This position calls for a renewed focus on transparency in technical development.

Meanwhile, practical evidence suggests that the effectiveness of machine learning-based solutions depends more on the intrinsic properties of input signals than on the algorithms themselves.[3] Factors such as physiological relevance, methods of signal acquisition and preprocessing, and the

extraction of key physiological features from the signals have a significant impact on the quality of classification outputs. Consequently, physiological signals are the key components in any AI-based sleep testing technology.[2,9,10] Rather than relying solely on machine learning-assisted clinical decisions, it is essential for physicians and technicians to develop expertise in biosignal interpretation. This requires a comprehensive understanding of the sensor technology, signal recording and processing, and signal interpretation within specific clinical contexts.

Among surrogate signals, the mandibular jaw movement (MJM) signal[11] stands out for its originality. The potential of MJM in sleep measurement was first explored by Miyamoto in 1998.[12] Over the last 15 years, extensive research has led to the establishment of MJM-based sleep testing technologies. However, despite the multiple advantages and demonstrated benefits in clinical practice of MJM signal, significant challenges persist in educating clinicians on the physiological mechanisms between MJM and sleep medicine, and the unique technical aspects of MJM-based technologies, especially when compared to more established technologies like photoplethysmography (PPG).

In response to these challenges, a scoping review was conducted to systematically evaluate the technical and physiological aspects of MJM-based technology and their contribution to enhancing signal proficiency for users. The literature analysis focused on four main research questions:

RQ1: Does the research and application of MJM-based technology comprehensively address essential aspects, including physiological research, machine learning development, and clinical validation?

RQ2: What physiological mechanisms allow MJM signal to accurately represent sleep stages and detect sleep-related breathing disturbances?

RQ3: How comprehensively do research articles on MJM analysis describe this technology?

RQ4: How feasible and effective is the manual interpretation of MJM signal for the identification of sleep stages and detection of apnea/hypopnea events?

The PPG-based technology was chosen as a benchmark for comparison because (1) it is a well-established technology for wearable sleep testing devices, (2) it has been developed on a similar timeline as MJM-based technology, and (3) it differs fundamentally from MJM in terms of technical and physiological mechanisms.

METHODS

This review was conducted following the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines for scoping reviews.[13] A comprehensive literature search was performed using the PubMed database, aiming to capture all studies that contributed directly to the research and development of sleep testing technologies based on MJM or PPG signals. Additionally, relevant guidelines that provide insights into signal interpretation within specific clinical contexts were included. This search was limited to publications from January 1998 to July 2024 to cover the development history of these two technologies.

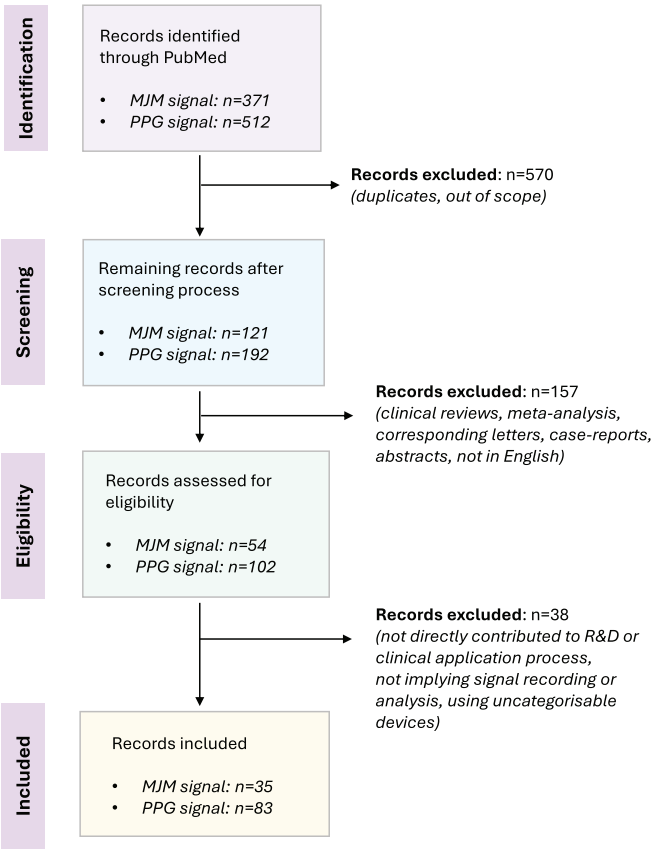

FIGURE 1 PRISMA flowchart describing the process of identification, screening, and selection of articles. MJM, mandibular jaw movement; PPG, photoplethysmography; R&D, research and development.

The identified records were initially screened to determine if they met the predefined inclusion and exclusion criteria. Following this, a detailed analysis and synthesis of the selected articles were performed based on a pre-established framework. More information on the literature search strategy, screening and selection criteria, as well as the literature review framework is available in the Supporting Information.

Literature search results

After completing the screening and selection processes, a total of 118 articles were included in the literature synthesis. This consisted of 35 articles related to the MJM signal[11,12,14–46] and 83 articles related to PPG technology.[47–129] A summary of the identification and selection processes is presented in Figure 1, and detailed specifications for each included article are available in the Supporting Information.

Two types of MJM-based devices were identified in the literature: a magnetometry-based device (Nomics, Liège, Belgium)[12,14–34] (22 articles) and a single-point contact sensor with an integrated accelerometer and gyroscope (Sunrise, Namur, Belgium)[35–46] (13 articles). Despite the differences in sensor technology, all MJM-related studies were analyzed together because they explore the same underlying physiological principle.

In contrast, studies on PPG technology were divided into two subgroups: consumer-grade devices (23 articles) and medical devices (60 articles). The consumer-grade device subgroup includes products such as smartwatches, rings, and finger-mounted units, primarily designed as sleep trackers rather than for OSA diagnosis. Notable devices in this category include the Fitbit (11 articles)[70,71,79,83,84,89,109,115,120] and the Oura ring (seven articles).[101,102,117] The medical device subgroup is primarily focused on the WatchPAT product line (46 articles),[51–59,64–69,107,121] which represents the majority of research and development in PPG technology in the field of sleep medicine. This subgroup also includes recently developed devices like NightOwl (five articles),[75,105,111,123,125] SleepImage (three articles),[81,103,124] and Belun (four articles).[90,113,126,128]

In this review, we focus exclusively on the MJM signal and provide comparative analyses with PPG-based technologies where applicable. The results of our literature synthesis are organized into four sections: (1) the comprehensiveness in the research, development and application of MJM-based technology; (2) the physiological significance of the MJM signal; (3) the technical transparency; and (4) the interpretability of the MJM signal.

Comprehensiveness in the research, development, and application of MJM-based technology

One of the key challenges limiting signal proficiency is the incomplete research and validation process. The development and application of a new signal should follow a structured approach involving three key research phases. First, basic research is needed to establish the physiological foundation, identifying potential applications of the signal. Second, engineering research should focus on optimizing sensor configurations and developing machine learning-based analytic solutions tailored to specific tasks. Finally, clinical research should assess the reliability and effectiveness of the technology when applied to a clinical context.

While all three phases are complementary and necessary, physiological and engineering studies are particularly crucial for building signal proficiency. These studies provide a comprehensive understanding of sensor configurations, physiological properties, signal processing methods, and interpretation processes. In contrast, clinical studies primarily focus on assessing final outcomes, often simplifying or omitting technical details. Limitations such as restricted access to raw data can further hinder the researcher's ability to display new signals alongside PSG channels or to allow for manual editing.

Furthermore, while clinical evaluation is essential, a true validation requires establishing relationships and causal links between surrogate signals and physiological events, such as those related to sleep or respiration. Distinction between "evaluation" and "validation" is crucial, as highlighted by de Zambotti et al.[130] on behalf of the National Sleep Foundation.

In the context of OSA diagnosis, the validation process involves multiple levels (Figure 2a). At the foundational level, the aim is to establish a relationship,[28,38] and ideally causality,[34] between a surrogate signal (such as MJM) and physiological events like breathing or motor events, or transitions between sleep stages. This is typically benchmarked against gold-standard signals like electroencephalography (EEG)[52,56,57] for sleep stages, and diaphragmatic electromyography (EMG),[28] or esophageal pressure (PES)[38] for respiratory events.

At an intermediate level, validation focuses on the epoch-by-epoch performance[22,37] of the core machine learning algorithm for classification tasks (e.g., sleep staging). Subsequently, a quantitative agreement analysis is required to compare the new technology against PSG, using the Bland–Altman method.[36,44] At the highest validation level, we evaluate the diagnostic accuracy of the automated analysis to support the diagnosis of OSA in clinical practice.[6,40]

It is important to note that success at one validation level does not guarantee positive outcomes at another. Achieving high accuracy in epoch-by-epoch classification does not necessarily translate to strong quantitative agreement in the Bland–Altman analysis, nor does it guarantee robust diagnostic performance. In addition, a functional machine learning solution does not automatically validate the physiological significance of a signal component.

The diagram in Figure 2b summarizes the research and development timeline for MJM and PPG signals in sleep testing, highlighting key achievements for each technology.

PPG is a non-invasive, optical-based method to measure volumetric changes in blood flow within the microvascular bed of the skin.[131,132] Developed in 1937, PPG was initially used predominantly for cardiovascular conditions.[132] Its application in sleep medicine is relatively new, with studies beginning around 1999.[131] Foundational studies on PPG include physiological and technical investigations by Hdener,[56] Schnall,[47] Pillar,[52] and Herscovici[57] on the WatchPAT device, often focusing on single components such as actigraphy (ACT),[56] peripheral arterial tone (PAT),[47] or pulse rate (PR).[50]

MJM has been studied since the 1970s in dentistry as an indicator of anatomical structure and motor function.[1] However, physiological studies by Hollowell,[133] Miyamoto,[12,14] and Senny[15] marked the beginning of MJM's application in sleep medicine, by revealing the significance of MJM signal amplitude changes during sleep. These studies bridged the fields of dentistry, respirology, and neurology.

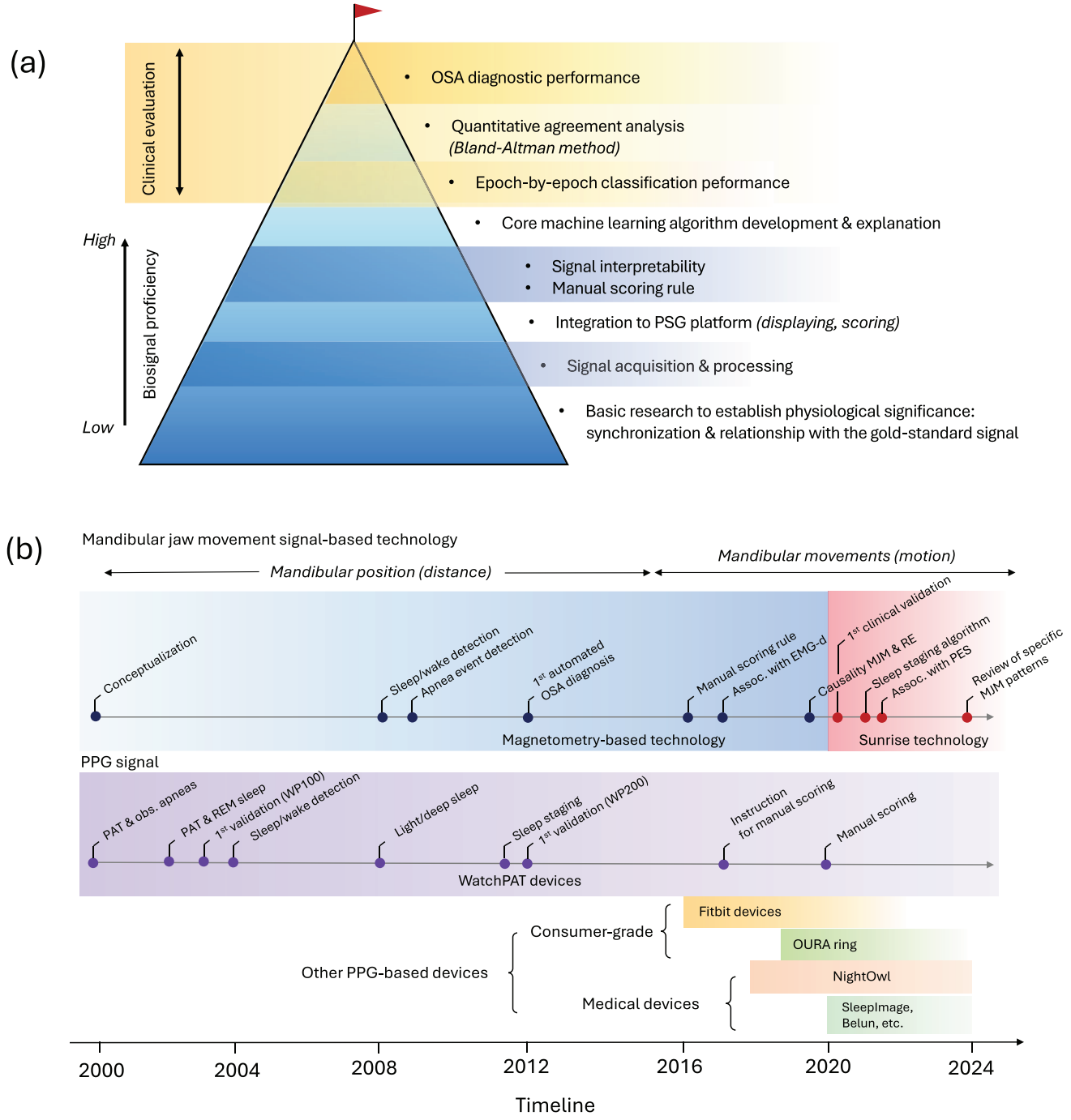

FIGURE 2 Multistep research and development path. (a) The diagram illustrates a pyramid representing the layers of knowledge surrounding an artificial intelligence-based signal analytic technology applied to clinical issues, such as OSA diagnosis. Research publications have often scratched the surface, leaving a substantial portion—encompassing technical details, physiological knowledge, and signal interpretation — unexplored. These hidden elements are essential for enhancing biosignal literacy. (b) Timeline of research and development for the MJM (upper) and PPG (lower) signals in sleep testing applications.

In 2008, Senny et al.[15,16] were the first to propose using machine learning with MJM signal to differentiate between sleep and wake states, as well as to detect sleep apnea events.

Our analysis (Table 1) shows that although the MJM-based technologies have fewer publications compared to PPG-based technologies, they demonstrate a more balanced approach to research and development. MJM studies are composed of 69.7% clinical, 18.2% physiological, and 12.1% engineering research. In comparison, PPG-based medical devices show proportions of 84.5% clinical, 6.9% physiological, and 8.6% engineering studies. Additionally, 91.3% of studies on consumer-grade PPG devices consist of clinical evaluations.

TABLE 1 Summary of literature review findings on MJM signal technology compared to PPG-based technology.

	MJM signal	PPG signal (Consumer-grade devices)	PPG signal (Medical devices)
Total included publications	$n = 35$	$n = 23$	$n = 60$
Category of publication			
Physiological studies	$n = 6$	$n = 0$	$n = 4$
Engineering studies	$n = 4$	$n = 2$	$n = 5$
Clinical studies	$n = 23$	$n = 21$	$n = 49$
Instruction/technical notes	$n = 2$	$n = 0$	$n = 2$
Clinical tasks			
Sleep/wake detection	$n = 4$	$n = 4$	$n = 3$
Sleep staging	Wake/NREM/REM: $n = 3$ Wake/LS/DS/REM: $n = 1$	Wake/NREM/REM: $n = 2$ Wake/LS/DS/REM: $n = 17$	LS/DS: $n = 1$ NREM/REM: $n = 7$ Wake/LS/DS/REM: $n = 2$
Respiratory event detection	$n = 7$	$n = 1$	$n = 4$
OSA screening/diagnosis	$n = 13$	$n = 0$	$n = 29$
OSA management	$n = 7$	$n = 0$	$n = 8$
Other clinical contexts	$n = 3$	$n = 0$	$n = 10$
Sensor technology	Magnetometry: $n = 22$ Acc + Gyr: $n = 13$	Acc + PPG: $n = 21$ PPG: $n = 1$ Acc + Gyr + PPG: $n = 1$	Acc + PPG: $n = 52$ PPG: $n = 5$ PPG + ECG: $n = 2$ Acc + PPG + ECG: $n = 1$
Device name	Nomics: $n = 20$ Sunrise: $n = 13$ Others: $n = 2$	Fitbit: $n = 11$ Oura: $n = 7$ Apple Watch: $n = 3$ Others: $n = 4$	WatchPAT: $n = 46$ NightOwl: $n = 5$ SleepImage: $n = 3$ Philips: $n = 1$ Belun: $n = 4$ Anne: $n = 1$
Signal configuration			
1 component	Mandibular distance: $n = 21$	$n = 0$	PAT: $n = 4$ HR/PR: $n = 1$
2 components	Mandibular distance + capnography: $n = 1$ MJM Acc + Gyr: $n = 13$	ACT + HR/PR: $n = 12$ ACT + PAT: $n = 4$ PAT + SpO2: $n = 1$	ACT + PAT: $n = 1$ ACT + HR/PR: $n = 1$ PAT + HR/PR: $n = 1$ HR/PR + SpO2: $n = 3$
3 components	$n = 0$	ACT + HR/PR + RR: $n = 5$ ACT + PAT + HR/PR: $n = 1$	PAT + HR/PR + SpO2: $n = 2$ ACT + PAT + SpO2: $n = 13$ ACT + PAT + HR/PR: $n = 3$ ACT + HR/PR + SpO2: $n = 4$ HR/PR + RR + SpO2: $n = 2$
>3 components	$n = 0$	$n = 0$	ACT + PAT + HR/PR + SpO2 + Snoring: $n = 21$ ACT + PAT + HR/PR + SpO2: $n = 4$ ACT + PAT + ECG + SpO2: $n = 1$
Signal pre-processing method	Comprehensive: $n = 4$ Not provided: $n = n = 22$ Summarized: $n = 7$	Comprehensive: $n = 1$ Not provided: $n = 19$ Summarized: $n = 3$	Comprehensive: $n = 1$ Not provided: $n = 18$ Summarized: $n = 3$
Interpretability			
Integrated to PSG for review/editing	Yes: $n = 21$ No: $n = 14$	Yes: $n = 0$ No: $n = 23$	Yes: $n = 18$ No: $n = 42$
Pattern visualization	Yes: $n = 24$ No: $n = 11$	Yes: $n = 4$ No: $n = 19$	Yes: $n = 16$ No: $n = 44$

(Continues)

TABLE 1 (Continued)

	MJM signal	PPG signal (Consumer-grade devices)	PPG signal (Medical devices)
Interpretation rule	None: $n = 22$ Summarized: $n = 6$ Detailed: $n = 3$ Visual: $n = 2$ Quantitative: $n = 4$	None: $n = 23$	None: $n = 72$ Summarized: $n = 9$ Detailed: $n = 1$ Visual: $n = 3$ Quantitative: None
Support for signal displaying and manual editing	Yes: $n = 25$ Unknown: $n = 10$	Yes: $n = 1$ No: $n = 22$	Yes: $n = 12$ No: $n = 35$ Unknown: $n = 11$
Manual interpretation applied as measurement method	Yes: $n = 12$ No: $n = 21$	Yes: $n = 0$ No: $n = 23$	Yes: $n = 7$ No: $n = 51$
Validation method			
Bland–Altman analysis	$n = 12$	$n = 21$	$n = 42$
EBE classification performance	$n = 7$	$n = 20$	$n = 7$
Diagnostic performance	$n = 11$	$n = 0$	$n = 33$

Abbreviations: Acc, accelerometer; ACT, actigraphy; DS, deep sleep; EBE, epoch-by-epoch; ECG, electrocardiography; Gyr, gyroscope; HR/PR, heart rate/pulse rate; LS, light sleep; MJM, mandibular jaw movements; (N)REM, (non-)rapid eye movement; OSA, obstructive sleep apnea; PAT, peripheral arterial tone; PPG, photoplethysmography; SpO2, oxygen saturation.

The development of MJM-based sleep testing technologies can be divided into two main periods, each marked by distinct sensor types: the magnetometry-based device (Nomics, Liège, Belgium) (2008–2020)[15–34] and the single-point contact sensor integrating an accelerometer and gyroscope (Sunrise, Namur, Belgium) (2020–2024).[35–46] Each period is characterized by extensive evidence demonstrating the physiological relevance and clinical utility of machine learning-based MJM analysis for sleep staging, OSA diagnosis,[15,26,36] and monitoring OSA therapy.[24,31,44]

The effectiveness of MJM analysis has been comprehensively evaluated across three key criteria: agreement with PSG scoring (12 studies),[16,19,21,26,35–37,40,44–46] epoch-by-epoch classification accuracy (seven studies),[15,16,22,27,33,36,37] and diagnostic ability (11 studies).[16,17,19,21,26,35,36,39,40,42,43] Notably, Senny et al.[19] and Pépin et al.[36] simultaneously evaluated all three criteria.

Physiological significance of the MJM signal

An AI-driven sleep analysis solution typically operates through several steps. First, sensors with minimal contact points on the body capture one or more physiological signals. Then, machine learning algorithms analyze input data to perform classification tasks, such as identifying sleep stages or detecting OSA-related respiratory events. Finally, from these classification outputs, clinical metrics like total sleep time (TST), apnea-hypopnea index (AHI), and arousal index (ArI) are derived.

As individuals transition through different sleep stages, coordinated changes occur within the central nervous system (CNS) and the autonomic nervous system (ANS) which regulate peripheral motor organs, respiratory functions, and cardiovascular systems. These autonomic fluctuations are reflected in physiological signals captured by different technologies including the MJM single-point contact sensor. Exploring the physiological relationship between signal variations and sleep activities is crucial for the effective application of AI-based sleep technologies.

Unlike conventional sleep testing methods like PSG, modern technologies do not directly measure electrical brain activity, airflow, or respiratory effort. Instead, they rely on one or more surrogate signals, which indirectly reflect the physiological processes. This surrogate nature of signals makes it challenging to fully understand the underlying physiological mechanisms. The SCOPER classification system[9] categorizes sleep testing devices based on six physiological components: sleep, cardiovascular, oximetry, position, effort, and respiratory. However, this classification alone does not fully explain the physiological activities associated with complex signals.

To understand the crucial role of the mandible (jaw) in maintaining upper airway (UA) patency during both normal and disturbed sleep, it is imperative to revisit UA dynamics during breathing. The UA, extending from the hard palate to the larynx, lacks rigid structural support, and includes a collapsible segment. This flexibility is essential for functions like speech and swallowing but creates potential challenges during sleep. Inspiration is driven by the diaphragm muscles generating negative pressure within the chest cavity. However, this negative pressure can also cause pharyngeal narrowing in the UA, leading to obstruction during sleep.[134]

Additionally, the transition from wakefulness to sleep is associated with reduced activity in the UA dilator muscles and an increase in UA resistances. Both central and reflex activations of these pharyngeal dilator muscles help maintain the airway open.[135] Indeed, the ventilation rate decreases

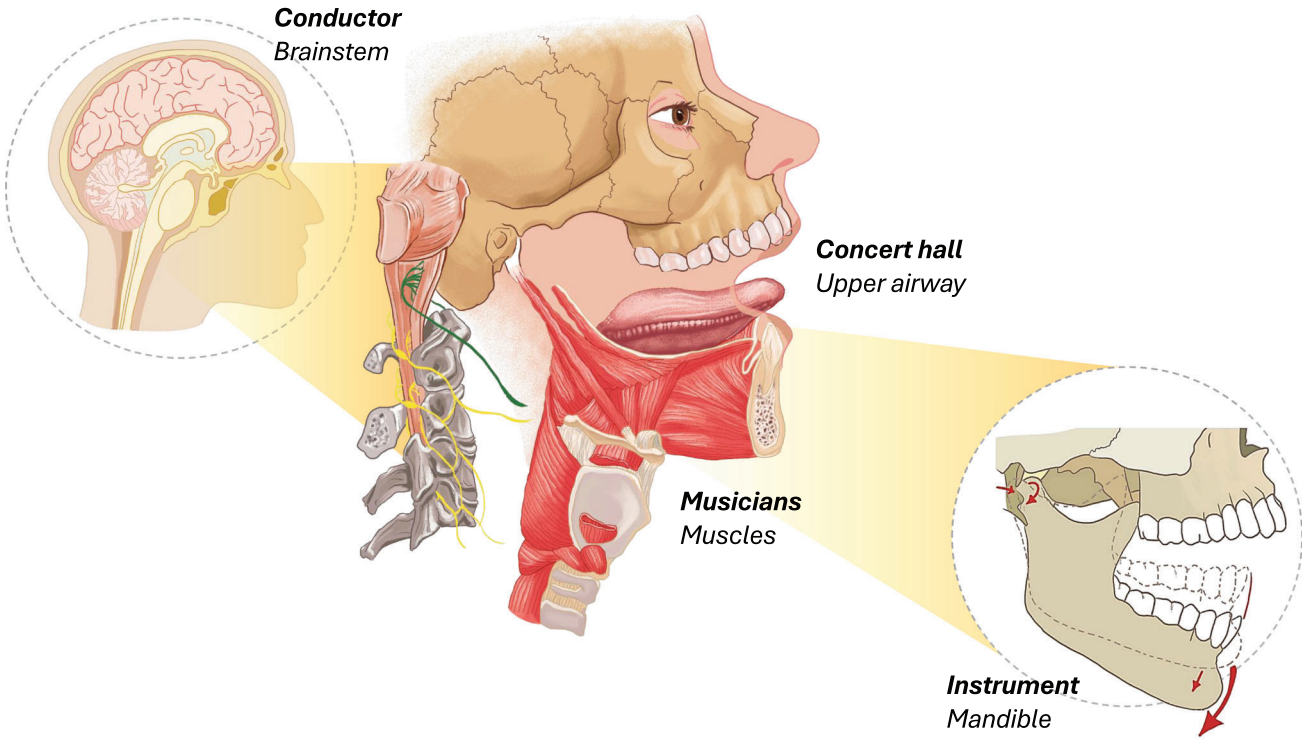

FIGURE 3 Metaphoric representation of the mandibular jaw's instrumental key role to stabilize the pharynx during sleep. The rhythmic respiratory movements of the mandibular jaw play a crucial role in maintaining pharyngeal stability during normal sleep. Functioning as an instrumental mobile bone, the mandibular jaw helps keep the upper airway (UA) open by modulating the craniofacial anatomy of the oral cavity. Monitoring mandibular jaw movements (MJM) during sleep enables precise tracking of small displacements, typically in the range of a few tenths of a millimeter. These movements are synchronized with breathing cycles and are orchestrated by the respiratory centers in the brain. The hyoid bone is stabilized by the posterior pharyngeal muscles, providing support to the oral floor muscles during the respiratory cycle. MJM mobilize muscles directly or indirectly via the hyoid bone, contributing to the overall UA stability. By exerting horizontal traction along the oral floor, MJM recruit pharyngeal muscles to stiffen the pharynx and counteract suctioning negative pressures in the UA, thereby preventing airway collapse during sleep.

during sleep, and CO_2 levels rise compared to wakefulness, triggering brainstem centers to increase UA dilator muscle activity during inspiration, from the nostrils to the upper and lower airways.[136]

The mandibular jaw plays a key role in this process, acting as a sensitive instrument that reflects delicate changes in rhythm and tempo of the brain's control over UA stability (Figure 3). Through its movements, the mandibular jaw helps strengthen the genioglossus muscle, an extrinsic muscle of the tongue, which prevents UA collapse during both normal and disturbed respiratory cycles. Originating from the mandibular symphysis and attaching to the hyoid bone and the entire length of the tongue, the genioglossus supports UA patency. However, during sleep, basal dilator muscle's tone decreases, and the genioglossus's phasic activity reduces, increasing UA resistance at sleep onset in both healthy individuals and OSA patients.[35]

As sleep deepens, the genioglossus activity progressively increases during non-rapid eye movement (NREM) sleep, reaching levels comparable to or even higher than those during wakefulness.[137] This increased activity correlates with a consistent rise in the peak-to-peak amplitude of MJM during deeper sleep stages (e.g., N3), reflecting the increase in UA resistances in normal individuals.[41]

Monitoring MJM is like placing a probe within the brainstem, providing valuable insights into the central drive to respiratory and UA muscles. This approach provides a comprehensive method for assessing sleep-related breathing disorders.[138,139]

Basic research has demonstrated strong correlations between changes in MJM properties, which reflect respiratory effort, and other reference signals like PES or diaphragmatic EMG. For instance, the MJM signal has been shown to closely mirror the patterns observed in EMG-d activity, clearly distinguishing between normal breathing, obstructive, mixed, and central respiratory episodes.[28] Additionally, Martinot et al. confirmed a causal relationship between vertical mandibular displacement and airflow amplitude.[34] A recent study further validated the high synchronization level between the MJM signal captured by the accelerometer and gyroscope-based sensor and PES, the gold-standard signal for quantitatively measuring respiratory effort.[38] Results also revealed that both PES and MJM signal amplitudes effectively differentiate between central and obstructive events, as well as between apneas and hypopneas.

Technical transparency

The design, structure, and placement of sensors play a crucial role in understanding the operating mechanisms and characteristics of each signal. For example, although PPG technology is often considered a single category, it actually encompasses a variety of distinct variants, each differing in construction, signal configuration, and interpretation methods.[131] PPG can indeed operate in either transmission or reflective modes, with variations in light wavelength and measurement location.[131] These factors can significantly impact the PPG waveform's shape, amplitude, signal-to-noise ratio, and sensitivity to motion artifacts.

The MJM signal can be recorded using two types of sensors. Initially, MJM signal recording relied on magnetometry (Nomics, Liège, Belgium),[15–34] which captures only the vertical mandibular position. In 2015, Martinot et al. expanded the concept from a basic measurement of jaw position to a more comprehensive analysis of mandibular movement.[25] A new generation of MJM sensors emerged in 2019, consisting of a single-point contact sensor with an integrated accelerometer and gyroscope (Sunrise, Namur, Belgium) designed to be attached to the chin.[35–46] This innovative technology offers multiple advantages, including wireless data transfer, more flexibility in sensor placement, an enhanced signal resolution, and fortified physiological data. The embedded inertial measurement unit of the sensor enables three-dimensional recording of MJM, and the gyroscope facilitates the precise measurement of mandibular rotation. These features provide a more detailed, sensitive, and multidimensional analysis of MJM frequency and amplitude.

Compared to PPG, MJM signal processing is often simpler, using a filtering frequency range of 0.15–0.6 Hz. This frequency range effectively captures the respiratory drive during sleep and is used across the different MJM sensor types.

Regardless of the type of sensor used, MJM analysis relies solely on the MJM. In contrast, PPG is a composite signal with two main components: a non-pulsatile baseline that reflects low-frequency oscillations caused by changes in capillary density (sympathetic tone) and venous volume variations (induced by respiration), and a pulsatile component that represents the systolic and diastolic phases of the cardiac cycle.[131] PPG also provides valuable physiological indicators for sleep testing, including PAT,[61,108] PR,[50] PR variability,[79,101] respiratory rate (RR),[71,103] and oxyhemoglobin saturation. In PPG-based multisensor systems, typically at least two signal components are used, with ACT[56] often being the primary component combined with one or more additional PPG channels.[131] The most common configuration consists of four components: ACT, PAT, PR, and SpO_2, as seen in the WatchPAT 200 device (21 studies), while the second most common setup (13 studies) includes ACT, PAT, and SpO_2.

While combining multiple signal components can improve overall performance by compensating for the limitations of each component, it also introduces complexity, making interpretation and manual review of raw data more challenging. Publications rarely provide systematic and clear guidelines for interpreting these combined signal patterns.[56,104,108] As a result, oversimplified validation results for multisensory devices may obscure the individual strengths and limitations of each signal, as well as their combined role within algorithms to handle tasks like sleep staging.

Assessing a complex multisensory device as a single sensor may also lead to misconceptions about the role of auxiliary components. It remains unclear whether integrating more channels improves sleep staging performance. Also, according to Alarcón et al.,[10] a combination of three signal components is sufficient to achieve optimal performance in diagnosing OSA, and adding more channels does not necessarily enhance diagnostic accuracy and may even lead to worse outcomes.

Interpretability of the MJM signal

For practitioners, developing proficiency in signal interpretation is essential for making well-informed decisions. This proficiency is built by exposure to various factors, such as illustrative examples of typical signal patterns,[11] written instructions,[36,58] flowcharts outlining the interpretation algorithm,[108] and quantitative interpretation rules.[25,26] Unfortunately, many clinical studies lack this transparency,[79,80,84] often performing validation only at an abstract level without providing detailed insights into the core algorithms or specific signal patterns that were analyzed.

By contrast, the interpretation algorithm for the WatchPAT device, a PPG-based technology, has been clearly and comprehensively described.[58,108] The scoring process begins by differentiating sleep from wake periods using the wrist ACT signal. Next, sleep periods are further classified as either NREM or REM sleep based on the PAT amplitude and PAT-derived inter-pulse intervals. Respiratory events are then identified during sleep periods by estimating likelihood functions based on the relationship between PAT amplitude reductions, PAT-derived pulse rate, and oxygen desaturation. A respiratory event is recognized based on one of three criteria: (1) a reduction in PAT amplitude combined with an increase in pulse rate or wrist activity; (2) a reduction in PAT amplitude alongside a desaturation of 3% or more; and (3) an oxygen desaturation of 4% or more. Only recently has PPG research explored the ability to differentiate between obstructive and central apnea events.[96,123]

Ability to identify sleep stages

Accurately identifying sleep stages is a fundamental yet challenging task for all AI-based sleep measurement devices. The earliest attempts at detecting sleep/wake states relied on ACT,[56] which has been recommended by the AASM since 2018 as an alternative to PSG for estimating sleep duration in clinical settings.[140] However, ACT struggles to

measure sleep metrics like TST, wakefulness after sleep onset (WASO), and sleep onset latency (SOL) with PSG-like precision due to inherent limitations.[141] Specifically, ACT detects movement rather than sleep stage per se, leading to potential inaccuracies as periods of lying awake without movement may be misclassified as sleep.[6] Additionally, ACT has also shown limited specificity in detecting WASO and inconsistency in estimating SOL, particularly in patients with insomnia or sleep disorders affecting motor function, such as restless leg syndrome.[142] After three decades of research, it seems unlikely that ACT technology alone will improve its ability to perform full sleep staging or will reliably detect true WASO, regardless of advancements in machine learning algorithms. Recent improvements in sleep staging have resulted mofrom integrating additional signal types than from optimizing algorithms.

In this context, the MJM signal, acquired with the single-point contact sensor, stands out for its unique ability to perform full sleep staging without requiring supplemental signals. Distinct MJM patterns corresponding to each sleep stage have been well described.[11] MJM reflects the activity changes in the trigeminal motor nucleus in relation to sleep/wake transitions controlled by cortical centers. During sleep, MJM oscillates at the breathing frequency (0.15–0.6 Hz) and becomes critically stable. Awakenings are marked by larger, unpredictable mandibular displacements.

From 2009 to 2012, Senny et al. conducted early experiments to develop algorithms capable of classifying wake/sleep states using only the MJM signal recorded by the magnetometric sensor.[16,19] The first algorithm[19] implied a fast wavelet transform combined with Shannon entropy measurement and achieved an accuracy level of 82.9%, and a measurement bias of 0.5 ± 1.4 h of sleep time. In a second study,[19] the feature set was expanded to include signal frequency and other metrics from complex analysis, resulting in a sensitivity of 85.3% but only moderate specificity (65.5%) for detecting sleep/wake states.

Later, specific MJM patterns captured by the single-point contact sensor with an integrated accelerometer and gyroscope became the basis for full sleep staging.[11] During the N1 stage, MJM exhibits cyclical patterns influenced by the ratio of theta/alpha waves seen on EEG, reflecting the connectivity between trigeminal motor nerves and respiratory centers in the brainstem. In the N2 stage, MJM oscillates at the respiratory frequency with small (several tenths of a millimeter), stable amplitudes. Deep sleep (N3 stage) is characterized by increased UA resistances, manifested by higher MJM amplitudes and greater stability compared to N2 sleep. REM sleep is, however, marked by irregular MJM patterns with lower amplitude and higher variability than during NREM sleep.

In 2020, a model based on the Random Forest algorithm and statistical features was developed to classify sleep/wake states using MJM signal captured by the sensor including an accelerometer and gyroscope.[38] Validated on 376 adult patients, this model showed good agreement with PSG in measuring TST, with a median measurement bias of −2.28 min and limits of agreement (LOAs) ranging from −38.3 to +36.7 min. In 2021, the first four-class sleep staging model was developed and validated.[37] This model classified 30-s epochs of MJM signal into awake, light sleep (N1 and N2), deep sleep (N3), and REM sleep. Using an extreme gradient boosting (XGBoost) classifier as the core algorithm, the model was trained on data from 800 OSA patients (451 men and 349 women). The input data comprised 217 features derived from the raw MJM signal, various filters with different frequency bands, moving averages, and statistical functions. Validated on an independent data sample of 226 OSA patients, the algorithm showed substantial agreement with manual PSG scorers (Kappa = 0.71 and accuracy = 78.3%) and a mean measurement bias for TST of −13.0 min (LOAs: −52.9 to +19.0).

Ability to detect sleep respiratory events

In addition to identifying sleep stages, the MJM signal is highly efficient in detecting respiratory effort[28,38] and discerning between central and obstructive events[33,38] as well as arousals.[11,36]

Under normal physiological conditions, MJM oscillates at the respiratory frequency (Figure 4). The amplitude of these displacements typically ranges between 0.2 and 0.3 millimeters during restful, eupneic breathing. During arousals, periods of rapid masticatory muscle activity, swallowing, or facio-mandibular myoclonus, MJM exhibits different changes in amplitude, shape, or frequency, which can be easily observed visually.[11]

Functioning as an instrumental mobile bone, the mandibular jaw plays a significant role in maintaining UA patency within the craniofacial structure of the oral cavity. Notably, patients with OSA tend to exhibit greater jaw opening during sleep compared to healthy individuals.

In essence, the amplitude of MJM signals reflects the level of respiratory effort or the activation of jaw muscles essential for ventilation. It is essential for the pharynx to stiffen before diaphragmatic contraction, as this action creates a decrease in airway pressure that can destabilize the pharyngeal structure. This negative pressure reflex is likely involved in the recruitment of trigeminal motoneurons and the resulting MJM, facilitated by brainstem inter-connectivity. Many pharyngeal muscles are attached to the mandible, either directly or indirectly via the hyoid bone, allowing the central drive to use the lower mandibular jaw as a fine-tuning lever to stiffen the upper airway muscles and maintain pharyngeal patency.

Clinical studies have demonstrated that machine learning-based MJM analysis achieves high reliability for both OSA diagnosis[36,40] and monitoring the AHI response during oral appliance therapy.[44] Recent studies using the single-point contact MJM sensor[35–37,40] have integrated a wide range of performance metrics including ROC AUC, sensitivity/specificity, positive/negative predictive values (PPV/NPV), and likelihood ratios (LR+/LR−) to provide a comprehensive evaluation of the accuracy of automated MJM analysis for diagnosing OSA.

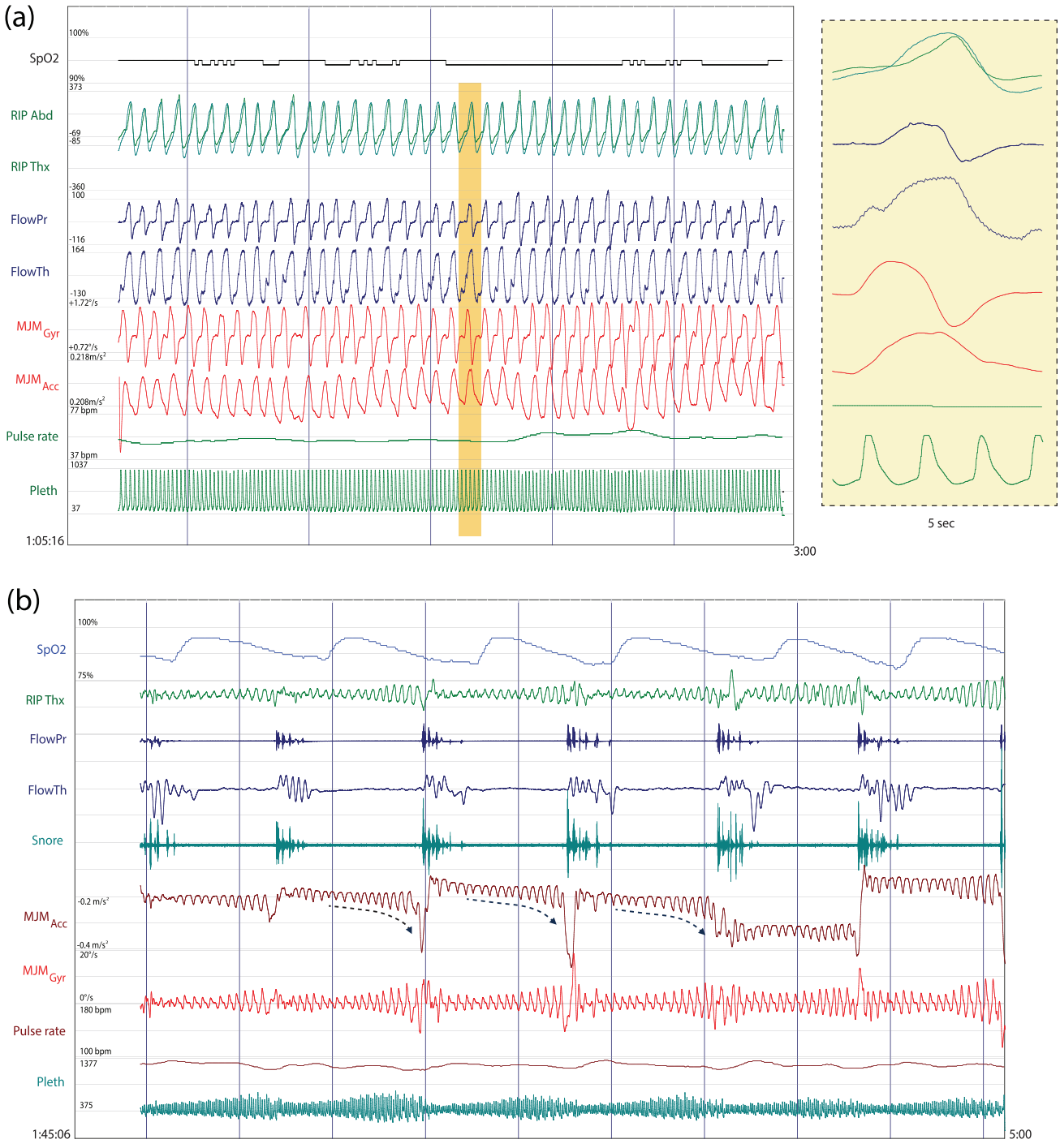

FIGURE 4 Comparison of MJM signal characteristics with other surrogate signals for monitoring respiration during sleep. (a) The respective changes during normal breathing are shown from top to bottom, including SpO_2, respiratory inductance plethysmography (RIP), nasal pressure, oro-nasal thermal flow, and mandibular jaw movements (MJM) recorded by the gyroscope (MJM-Gyr) and accelerometer (MJM-Acc) channels, pulse rate, and peripheral arterial tonometry (PAT). MJM are synchronized with the breathing frequency, as shown in this 3-minute fragment of polysomnography (PSG) recording. Governed by the motor trigeminal centers, MJM maintain pharyngeal patency, facilitating airflow, and support related ventilatory movements necessary for oxygenation; this is known as the respiratory activity of themandible. The zoomed-in section depicts one respiratory cycle, illustrating how the accelerometer detects mouth closure during ventilation and airflow movements. (b) A 5-minute PSG fragment depicting typical changes in mandibular position during obstructive episodes in an apneic patient. As the respiratory drive increases, the MJM-Gyr signalaligns with the RIP belts, capturing diaphragm ventilation. During obstructive apneas/hypopneas, the depressor muscles of the mandible are recruited earlier than the elevator muscles, as they are more sensitive to changes in blood CO_2 levels caused by reduced airflow. This leads to destabilization of the mandibular position and mouth opening (shown by the arrow - the more negative the signal, the wider the mouth opens) until a cortical arousal occurs, closing the mouth and peaking the flow.

Beyond its clinical effectiveness, the simplicity of interpreting the MJM signal sets it apart from other technologies. The MJM signal offers clear and straightforward guidelines for identifying respiratory events and can be displayed and interpreted like any standard signals that reflect PES changes, such as airflow, oxygen saturation, or RIP belts. MJM signal variations in shape, frequency, and amplitude correspond to different sleep stages and types of breathing disturbances.[11] In most cases, interpretation of MJM relies on amplitude profiles,[24,26,32,38] with an increase in amplitude during obstructive events and a decrease during central events.[33,38] The increase in amplitude can be stable or variable (reflecting trigeminal drive rate variability), or progressively rising over time.[25,26]

A typical obstructive event identified with the accelerometer and gyroscope sensor begins with an increase in respiratory drive, reflected by a rise in peak-to-peak MJM amplitude at the respiratory frequency, followed by a brisk movement closing the mouth at the end of the event. The differentiation is clear with arousals marked by MJM peaks showing significant accelerations (exceeding 0.10 m/s^2) compared to sleep intervals with respiratory effort. These intervals are defined by successive MJM peaks with peak-to-peak angular velocities exceeding 2°/s, synchronized with the respiratory rate. Detailed and systematic illustrations of these MJM signal patterns have been recently published.[11,41]

Application of manual interpretation

Manual interpretation of biosignals plays a crucial role in sleep diagnostics. It not only enables the assessment of plausibility and complexity in classification tasks, supporting the successful development of machine learning models, but also gives users a deeper understanding of the underlying mechanisms before these models are employed.

Regardless of the technology used, MJM recordings are well-known for their seamless integration into clinical settings. MJM acquisition and analysis have consistently been performed using the two aforementioned capturing devices, throughout all stages of research, from basic physiology studies,[14,17,18,34,38] to machine learning experiments[15,16,33,37] and clinical studies.[22,25,35,36,44] As early as 2008, the MJM signal was integrated into PSG recording software as a surrogate for conventional respiratory signals.[15–22] Since then, the visual display of specific MJM patterns alongside conventional PSG signals have become common in clinical research. This integration allows researchers to establish clear evidence of synchronization, relationships, and, ultimately, equivalence between MJM as a surrogate signal and other referential signals in sleep medicine.

Manual interpretation has been the primary method in nine of the 23 clinical studies involving MJM signal,[12,14,16,20,22–26,28,29,31] a higher number compared to PPG signal, which used manual interpretation in only three out of 49 studies.[100,114,129] Notably, between 2015 and 2018, several clinical studies on OSA diagnosis and treatment systematically applied manual interpretation to MJM signal.[25,26,28,29]

Unlike the MJM signal, manual interpretation of the PPG signal has only been explored recently. In two clinical studies by Zhang et al.[100] and Tschopp et al.,[129] both utilizing the WatchPAT 200 device, it was found that manual scoring and editing improved the accuracy of PAT signal interpretation for both sleep staging and OSA diagnosis.

DISCUSSION

The integration of AI into the analysis of new surrogate signals represents a natural evolution, rather than a radical shift, in the field of sleep and respiratory physiology. By leveraging advanced technologies, we extend the traditional methods of studying physio-pathological processes through biosignals like MJM or PPG, thereby enhancing our understanding of these signals. This review underscores the crucial role of signal proficiency in research and development as a fundamental condition for broader dissemination of physiological knowledge and for optimizing clinical benefits.

The growing adoption of AI in clinical practice brings both opportunities and challenges. A key challenge is the lack of technical proficiency among healthcare professionals, which can limit the effective interaction between users and these technologies. There is increasing interest in bridging the gap between engineering and medical research. In this context, this review aligns with previous interdisciplinary efforts that explored the application of machine learning in healthcare services,[143] the advancement of PPG signal technology,[131] and the focus on explainability in AI-driven medical imaging.[144]

Based on the analyses presented in this review, several approaches for future research are suggested. First, the development of technologies based on new biosignals should maintain a reasonable balance between physiological, engineering, and clinical studies. Second, scientific publications should prioritize technical transparency, including consistent terminology and detailed information on sensor configuration, operational mechanisms, and interpretation rules. In cases where multiple signal components are used, technology providers should clarify the physiological significance of each component and provide evidence of performance improvements from adding more channels. Third, machine learning-based research should support users in developing manual interpretation skills. This can be achieved through visual aids, written instructions, and other resources that help users identify specific signal patterns and interpret signal waveforms in clinical contexts.

CONCLUSION

An effective AI-based clinical solution should rely on signals that are easy to acquire, have a strong correlation with the underlying physiological process, and, most importantly, are

straightforward and easy to interpret. Researchers are encouraged to enhance technical transparency by providing deeper insights into signal properties and to follow a comprehensive research pathway.

The MJM signal, with its intrinsic advantages, meets the criteria for ideal signal literacy. These criteria include a solid physiological foundation, good reproducibility, seamless integration with PSG manual scoring processes, and clear interpretability. Furthermore, the MJM signal has undergone rigorous research and validation at all levels, making it a model for the research and development of new surrogate biosignals. By equipping clinical practitioners with a better understanding of these technologies, we empower them to make more informed clinical decisions, ultimately improving the management of OSA.

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CONFLICT OF INTEREST STATEMENT

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SUPPORTING INFORMATION

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