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ORIGINAL RESEARCH

Diagnosing OSA and Insomnia at Home Based Only on an Actigraphy Total Sleep Time and RIP Belts an Algorithm "Nox Body Sleep™"

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Purpose: The COVID-19 pandemic has influenced clinical sleep protocols with stricter hospital disinfection requirements. Facing these new rules, we tested if a new artificial intelligence (AI) algorithm: The Nox BodySleep™ (NBS) developed without airflow signals for the analysis of sleep might assess pertinently sleep in patients with Obstructive Sleep Apnea (OSA) and chronic insomnia (CI) as a control group, compared to polysomnography (PSG) manual scoring.

Patients-Methods: NBS is a recurrent neural network model that estimates Wake, NREM, and REM states, given features extracted from activity and respiratory inductance plethysmography (RIP) belt signals (Nox A1 PSG). Sleep states from 139 PSG studies (CI N = 72; OSA N = 67) were analyzed by NBS and compared to manually scored PSG using positive percentage agreement, negative percentage agreement, and overall agreement metrics. Similarly, we compared common sleep parameters and OSA severity using sleep states estimated by NBS for each recording and compared to manual scoring using Bland-Altman analysis and intra-class correlation coefficient.

Results: For 127,170 sleep epochs, an overall agreement of 83% was reached for Wake, NREM and REM states (92% for REM states in CI patients) between NBS and manually scored PSG. Overall agreement for estimating OSA severity was 100% for moderate-severe OSA and 91% for minimal OSA. The absolute errors of the apnea–hypopnea index (AHI) and total sleep time (TST) were significantly lower for the NBS compared to no scoring of sleep. The intra-class correlation was higher for AHI and significantly higher for TST using the NBS compared to no scoring of sleep.

Conclusion: NBS gives sleep states, parameters and AHI with a good positive and negative percentage agreement, compared with manually scored PSG.

Keywords: PSG, chronic insomnia, OSA, machine learning, automatic sleep staging, artificial intelligence

Introduction

The use of in-laboratory polysomnography (PSG) and Home Sleep Apnea Tests (HSATs) in the diagnosis of obstructive sleep apnea (OSA) has been well defined for decades.

In the last edition of the American Academy of Sleep Medicine's (AASM) technician manual,[1] and in the technical guidelines for the Evaluation, Management and Long-term Care of OSA in Adults,[2] the two accepted methods of objective testing for OSA are indeed PSG and HSAT. Furthermore, according to the Adult OSA Task Force of the AASM, HSAT may be used to diagnose OSA in patients with a high pretest likelihood of moderate to severe OSA when utilized as part of a comprehensive sleep evaluation.[2] However, HSAT testing alone is not recommended in patients with major comorbid conditions like: moderate to severe pulmonary disease, neuromuscular disease, or congestive heart failure, or those suspected of having a comorbid sleep disorder. It is less sensitive/specific than in-lab PSG, due to the lack of evaluation of total sleep time (TST), which allows calculating a real index of apnea hypopnea/hour.

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Using PSG for evaluating OSA involves recording the following physiological signals: electroencephalogram (EEG), electrooculogram (EOG), chin electromyogram (EMG), oronasal flow, oxygen saturation, respiratory effort, and electrocardiogram (ECG) or heart rate. Additional recommended parameters are body position and leg EMG derivations. Tibialis anterior EMG is useful in detecting leg movement and periodic limb movement disorders (PLMD), which coexist with sleep-disordered breathing (SDB) in many patients. PSG studies are usually conducted in a sleep lab facility, under the supervision of trained sleep technologists who are present throughout the study to monitor technical adequacy and patient compliance.

HSAT is much simpler and less expensive than PSG. It includes at least the recording of airflow, respiratory effort, and blood oxygenation. The recommended biosensors used to monitor these parameters for HSAT are the same as for PSG: an oronasal thermal sensor to detect apnea, a nasal pressure transducer to measure hypopnea, oximetry, and calibrated or uncalibrated respiratory inductance plethysmography (RIP) for respiratory effort. The device can be self-applied by the patient. The role of a trained sleep technician technologist is also essential to apply the portable monitoring (PM) sensors, or assist the patient in correctly applying the sensors.

Due to the worldwide COVID-19 pandemic, many countries have provided recommendations on how to ensure the safety of performing PSG and HSAT studies for diagnosing OSA. During the pandemic, sleep diagnostic routines were changed drastically in Europe. Prior to the pandemic, almost 100% of PSG were performed in sleep centers. However, in-lab PSG and home sleep testing decreased from 93%/88% before COVID-19 to 20%/33%, respectively. Sleep medicine services were reduced by 50–90% during the first 10–12 months of the COVID-19 pandemic. In addition, in-house procedures such as in-lab PSG or positive airway pressure titrations were reduced or not performed at all, or only limited to highly selected patient groups.[3]

Adequate access to sleep diagnostic testing is of particular importance for individuals with OSA given that the condition is associated with increased risk of adverse outcomes in patients with COVID-19.[4,5] As a result, some researchers recommend using the Sleep Symptom Checklist and a range of other self-reported measures in lieu of in-laboratory testing to screen for and cope with OSA in general practice.[6]

Another important approach to facilitate the diagnosis of OSA is the application of analytical methods involving artificial intelligence (AI) to PSG data. Numerous teams, including our group, have proposed algorithms that would allow easier and more accurate diagnosis of sleep disorders based on PSG data.[7–10]

In addition to patients with OSA, those with chronic insomnia (CI), the most prevalent sleep disorder affecting 10–20% of the general population, were also particularly affected by the pandemic.[11] Numerous patients suffering from CI come to our lab for care and are mainly proposed to receive cognitive-behavioral therapy for insomnia (CBT-I), the gold-standard reference treatment. According to the International Classification of Sleep Disorders (ICSD-3) criteria,[1] PSG is not indicated in routine evaluation for CI but may be useful to exclude other sleep disorders (such as OSA and Periodic Limb Movement Disorders (PLMD). Performing a PSG is not mandatory to change the clinical perspective of the physician proposing CBT-I. However, before the COVID-19 pandemic we recorded one night of in-lab PSG in patients with severe CI before starting CBT-I in order to exclude patients with OSA and RLS to better define the phenotype of patients with severe CI.

Facing the challenges of diagnosing and taking care of patients during the COVID-19 pandemic we decided to determine retrospectively the feasibility of a simplified approach to diagnosing OSA and CI as a control group without relying on the traditional PSG neurophysiological signals.

The rationale of our study was to test how an AI algorithm can be used to diagnose OSA and CI in a clinical setting and to justify the opportunity for easier diagnostic methods to be applied outside clinical facilities.

Methods

Participants

The PSG dataset consists of 182 initial ambulatory and laboratory PSG recordings provided by the Sleep and Vigilance of the Hôtel-Dieu Hospital of Paris (SVHD) (France). The PSG recordings were performed using the Nox A1 (Nox Medical®, Reykjavik, Iceland).

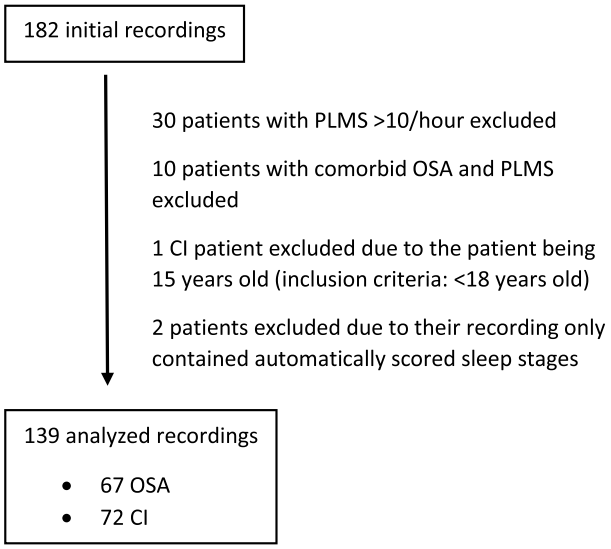


Figure 1 Diagram that describes the data flow.

We retrospectively analyzed PSG recordings from 139 patients who met the inclusion/exclusion criteria as mild, moderate, and severe OAS and CI (initial insomnia (sleep onset), sleep maintenance insomnia, and too-early awakening insomnia).

Thirty patients were excluded with a diagnosis of PLMD >10/hour. For further information regarding exclusion of patients from the analysis, see flow chart Figure 1. From the 139 included patients, 72 were suffering from CI and 67 from OSA (see Characteristics in Table 1). All the patients included retrospectively in this study complained, during their visit to the SVHD, of CI or OSA according to ICSD-3 criteria [AASM, 2014]. We systematically registered all patients by an ambulatory or laboratory PSG, independently of the suspicion of comorbidities. After PSG, medical doctors of the SVHD gave diagnoses to the patients during a post-PSG visit.

Table 1 Patient Characteristics of Both OSA and CI Cohorts Separately and Together

	OSA Patients (N=67)	**CI Patients (N=72)**	**Both Patient Groups (N=139)**
Sex [female/male]	24 / 43	52 / 20	76 / 63
Age [years]	54.0 ± 14.2 (21.0–90.0)	45.3 ± 12.7 (19.0–80.0)	49.5 ± 14.1 (19.0–90.0)
Height [cm]	172.9 ± 9.7 (148.0–195.0)	167.8 ± 8.9 (150.0–196.0)	170.3 ± 9.6 (148.0–196.0)
Weight [kg]	89.8 ± 21.8 (46.0–155.0)	65.7 ± 14.8 (38.0–120.0)	77.3 ± 22.1 (38.0–155.0)
BMI [kg/m2]	29.9 ± 6.2 (18.4–49.5)	23.2 ± 4.8 (16.4–46.9)	26.4 ± 6.4 (16.4–49.5)
AHI [/hrs]	62.9 ± 31.9 (8.3–159.5)	6.2 ± 3.6 (0.0–16.2)	33.5 ± 36.1 (0.0–159.5)
Analysis duration [min]	452.1 ± 71.0 (324.5–654.1)	470.1 ± 68.1 (329.9–703.2)	461.4 ± 69.8 (324.5–703.2)

Notes: Characteristics are represented in the following form when appropriate: mean ± standard deviation (min-max).
Abbreviations: BMI, body mass index; AHI, apnea-hypopnea index.

For CI, we excluded other sleep comorbidities based on PSG recordings and according to the AASM[1] guidelines: patients with OSA (AHI/hrs >10) and PLMD (PLM index/hour >10)).

PSG Recordings

We performed PSG recordings according to the AASM guidelines using the 2.6 version manual.[1] The Nox A1 System is an ambulatory, full polysomnography system, fully compliant with the AASM standards[12] and included: (i) 6 EEG derivations at frontal (F3/F4), central (C3/C4) and occipital (O1/O2) sites referenced to the contralateral mastoid, (ii) 2 EOG derivations, (iii) 3 EMG derivations placed on the chin (N = 1) and legs (N = 2). Respiratory parameters were respiratory flow, thoracic and abdominal RIP bands, oxygen saturation), and included body movements (position sensor).

Sleep Scoring

We visually scored each PSG according to the AASM guidelines[1] with the Noxturnal 5.1.3.203.88 software (Nox Medical®, Reykjavik, Iceland) where every 30 second epochs were scored blindly by 2 senior sleep technicians and classified stages as follows: wake, non-REM stage [N1, N2, N3] and REM sleep. Two certified sleep physicians reviewed the manual scoring data. We also scored arousals, leg movements, respiratory events, and periods of wake in order to calculate WASO (Wake After Sleep Onset).

Then, we calculated standard parameters based on individual hypnograms describing the macro-structure of sleep: TST, WASO, each sleep stage duration and Sleep Efficiency (SE).

Assessment of Sleep Disorders

While scoring, the sleep technicians visually identified sleep apnea according to AASM definitions.[1] Apnea was defined as a respiratory flow below 10% for more than 10 seconds and hypopnea a >30% decrease in respiratory flow associated with one arousal or an oxygen desaturation of more than 3% and for more than 10 seconds. We used thoracic and abdominal RIP band signals to categorize these events as "central", "obstructive" or "mixed". We also identified Periodic leg movements (PLM) whenever 4 leg movements were observed over a period of 90 seconds.

Nox BodySleep™, Algorithm (See for Entire Description)

Nox BodySleep 1.0 is an automatic sleep-staging model designed to classify 30 seconds epochs from common HSAT signals into sleep states WAKE, NREM, and REM. To classify a whole HSAT recording with Nox BodySleep, the recording is split into 30-second epochs, and features are extracted from RIP and actigraphy signals for each one of those epochs. Nox Medical designed these features to capture physiological changes occurring during different sleep states, and other features reflecting statistical properties of respiration and respiratory rate (respiratory rate variability, abdomen and thorax contributions, flow rate, tidal volume, and movement from accelerometer). For each epoch, the corresponding features are passed into a recurrent neural network model, which returns probabilities of the epoch belonging to sleep states WAKE, NREM, and REM.[8]

Manually scored sleep stages were converted to sleep states by grouping stages NREM1, NREM2, and NREM3 into a single NREM category. The agreement between sleep states scored using Nox BodySleep versus manually scored sleep states was quantified using the Positive Percentage Agreement (PPA), the Negative Percentage Agreement (NPA), and the Overall Percentage Agreement (OPA) metrics. Furthermore, 95% confidence intervals were bootstrapped for these metrics.

In this study, we define OSA severity as the classification of apnea–hypopnea indices (AHI) into three categories: AHI <5/hr, 5≤ AHI<15, and AHI ≥15. PPA, NPA, and OPA were used for quantifying the agreement of OSA severity estimated, when using Nox BodySleep total sleep time and sleep states, with manually scored respiratory events versus the OSA severity estimated using manually scored sleep states and respiratory events. To provide a baseline, we also calculated the PPA, NPA, and OPA for quantifying the agreement of OSA severity estimated using only manually scored respiratory events versus the OSA severity estimated using manually scored sleep states and respiratory events. Standard 95% confidence intervals were bootstrapped for these metrics.

To determine the agreement of the AHI produced using sleep states estimated by Nox BodySleep and manually scored respiratory events versus the AHI produced using manually scored sleep states and respiratory events, we performed Bland-Altman analysis and computed the intraclass correlation coefficient (called ICC: 2,1). To provide a baseline, we performed the same analysis on AHI estimated with only manually scored respiratory events versus the AHI estimated using manually scored sleep states and respiratory events. Statistical significance was investigated by pairwise comparison of absolute errors and bootstrapping.

To determine the interrater reliability (ICC (,1) of TST, SE, and WASO using sleep states estimated by Nox BodySleep versus the corresponding parameters produced using manually scored sleep states, we performed Bland-Altman analysis.

Ethics

This protocol followed the principles expressed in the Declaration of Helsinki of 1975, revised in 2001. The referred ethics committee (Comité de Protection des Personnes (CPP Paris Ile de France II, France) approved this retrospective analysis of PSG data of patients and controls. Patient data were treated anonymously according to the legal requirements of the Commission Informatique et Liberté (CNIL). All the patients entering our center at the period of the study signed an informed consent explaining the survey and approving that their PSG data would be treated anonymously and might be analyzed in order to improve the digital diagnosis of sleep disorders.

Results

Patient's Characteristics

Table 1 shows patients' characteristics and general PSG data. In general, patients diagnosed with OSA had a severe disease with an average AHI of 62.9 ± 31.9 (8.3–159.5). The time in bed for each recording was greater than 7 hours in each patient group, with an average analysis duration of 461.4 ± 69.8 (324.5–703.2) minutes.

Sleep States

Table 2 shows the agreement between manual sleep scoring and Nox BodySleep results regarding sleep states, based on 127,170 30-second epochs. The overall agreement was always equal to or above 0.8 with a maximum 0.92 for REM states in CI patients.

Table 2 Epoch-Level Sensitivity and Specificity of Scoring Sleep States Using Nox's BodySleep Compared to Manually Scored Sleep States, Alongside 95% Confidence Intervals Bootstrapped on a Patient-Level

		Total Epochs	Positive Agreement	Negative Agreement	Overall Agreement
OSA Patients (N=67)	**Wake**	12,165	0.54 (0.48, 0.60)	0.95 (0.94, 0.96)	0.87 (0.85, 0.89)
	NREM	40,449	0.91 (0.89, 0.92)	0.54 (0.49, 0.59)	0.79 (0.76, 0.81)
	REM	7513	0.46 (0.37, 0.55)	0.96 (0.95, 0.97)	0.90 (0.88, 0.91)
	Total	60,127	0.78 (0.75, 0.80)	0.68 (0.64, 0.71)	0.82 (0.80, 0.84)
CI Patients (N=72)	**Wake**	15,029	0.57 (0.50, 0.63)	0.96 (0.95, 0.97)	0.88 (0.85, 0.90)
	NREM	40,139	0.93 (0.91, 0.94)	0.66 (0.61, 0.70)	0.82 (0.80, 0.84)
	REM	11,875	0.71 (0.65, 0.76)	0.97 (0.95, 0.97)	0.92 (0.91, 0.93)
	Total	67,043	0.81 (0.78, 0.83)	0.78 (0.75, 0.81)	0.85 (0.83, 0.86)
Both patient groups (N=139)	**Wake**	27,194	0.55 (0.51, 0.60)	0.96 (0.95, 0.97)	0.87 (0.86, 0.89)
	NREM	80,588	0.92 (0.90, 0.93)	0.61 (0.58, 0.64)	0.80 (0.79, 0.82)
	REM	19,388	0.61 (0.56, 0.66)	0.96 (0.96, 0.97)	0.91 (0.90, 0.92)
	Total	127,170	0.79 (0.77, 0.81)	0.74 (0.71, 0.76)	0.83 (0.82, 0.85)

AHI and TST

Table 3 (a to d) shows the agreement of estimating OSA, using the two methods among three severity classes: minimal OSA (AHI < 5), mild OSA (5≤ AHI ≤ 15), and moderate to severe OSA (AHI >15). The analysis in Table 3 included sleep states estimated from Nox BodySleep, while the analysis presented in Table 4 did not use sleep states estimated from Nox BodySleep. The overall agreement was better when using sleep states estimates. Confusion matrix for estimating OSA with and without estimated sleep states is presented in Tables 5 and 6.

Overall, the average AHI was lower (but not clinically different) with manual scoring compared with Nox's BodySleep estimates (Table 7).

Table 3 Sensitivity and Specificity of Estimating Sleep-Disordered Breathing (SDB) Severity Using Estimated Sleep States from Nox's BodySleep Compared to Estimating SDB Severity Using Manually Scored PSG Sleep Stages

	Both Patient Groups (n=139)			
	Total Patients	**Positive Agreement**[Erreur! Signet non défini.]	**Negative Agreement**[Erreur! Signet non défini.]	**Overall Agreement**[Erreur! Signet non défini.]
Minimal SDB (AHI <5)	29	0.93 (0.82, 1.00)	0.91 (0.85, 0.96)	0.91 (0.86, 0.96)
Mild SDB (5≤ AHI ≤15)	43	0.77 (0.63, 0.89)	0.98 (0.95, 1.00)	0.91 (0.86, 0.96)
Moderate to severe SDB (AHI ≥15)	67	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)
Total	139	0.91 (0.86, 0.96)	0.97 (0.96, 0.99)	0.96 (0.92, 0.98)

Note: Each value is accompanied by bootstrapped 95% confidence intervals.

Table 4 Sensitivity and specificity of estimating sleep-disordered breathing (SDB) severity estimated without sleep staging compared to estimating SDB severity using manually scored PSG sleep stages

	Both patient groups (n=139)			
	Total Patients	**Positive Agreement**[Erreur ! Signet non défini.]	**Negative Agreement**[Erreur ! Signet non défini.]	**Overall Agreement**[Erreur ! Signet non défini.]
Minimal SDB (AHI <5)	29	0.69 (0.52, 0.85)	0.93 (0.88, 0.97)	0.88 (0.82, 0.93)
Mild SDB (5≤ AHI ≤15)	43	0.79 (0.66, 0.91)	0.91 (0.84, 0.96)	0.87 (0.81, 0.92)
Moderate to severe SDB (AHI ≥15)	67	1.00 (1.00, 1.00)	0.99 (0.95, 1.00)	0.99 (0.98, 1.00)
Total	139	0.87 (0.81, 0.92)	0.95 (0.92, 0.97)	0.93 (0.89, 0.96)

Table 5 Confusion Matrix for Estimating SDB Severity Using Sleep States Estimated from Nox's BodySleep Compared to Estimating SDB Severity Using Manually Scored Sleep Stages

		Nox's BodySleep		
		AHI <5	**5≤ AHI ≤15**	**AHI ≥15**
Manual PSG with sleep staging	**AHI <5**	27	2	0
	5≤ AHI ≤15	10	33	0
	AHI ≥15	0	0	67

Table 6 Confusion Matrix for Estimating SDB Severity Without Sleep Staging Compared to Estimating SDB Severity Using Manually Scored PSG Sleep Stages

		Manual PSG Scorings Without Sleep Staging		
		AHI <5	5≤ AHI ≤15	AHI ≥15
Manual PSG with sleep staging	AHI <5	20	9	0
	5≤ AHI ≤15	8	34	1
	AHI ≥15	0	0	67

Note: Each value is accompanied by bootstrapped 95% confidence intervals.

Table 7 Summary Statistics Mean ± Standard Deviation (Min-Max) for Each Scoring Overall Recordings

	AHI [/hrs]	Total Sleep Time [m]
Manually scored	31.03 ± 33.47 (0.20–164.10)	388.07 ± 65.93 (231.00–535.00)
Nox BodySleep	33.55 ± 35.92 (0.00–159.50)	361.18 ± 75.11 (112.50–528.00)
Manually scored without sleep staging	29.72 ± 30.86 (0.50–156.60)	454.52 ± 67.56 (324.50–689.70)

Note: One-way repeated measures analysis of variance was performed using the Friedman test.

Table 7 shows the differences regarding TST when estimated by manual scoring vs Nox's BodySleep and manual scoring vs manual scoring with no sleep stages. These differences are detailed in Figure 2 which describe AHI, TST, SE and WASO scatter plots and Bland-Altman plots from manually scored recordings vs recordings scored with the Nox BodySleep algorithm, in patients with OSA and with CI, respectively.

Table 8 shows that the median pairwise difference in the absolute error of the AHI and TST of manual scoring vs Nox BodySleep and manual scoring vs manual scoring with no sleep stages is statistically significantly lower when using the Nox BodySleep than when no sleep scoring is performed.

We calculated the AHI by two different methods according to two possible conditions of recording: 1) Polysomnography where AHI is defined as the number of apnea and hypopnea events per hour of real sleep. It is the gold standard method for the calculation of the AHI; 2) Nox BodySleep which solely relies on signals from Nox RIP belts and actigraphy to determine sleep time. Where the AHI corresponds to the number of apnea and hypopnea events per hour of sleep estimated by Nox BodySleep.

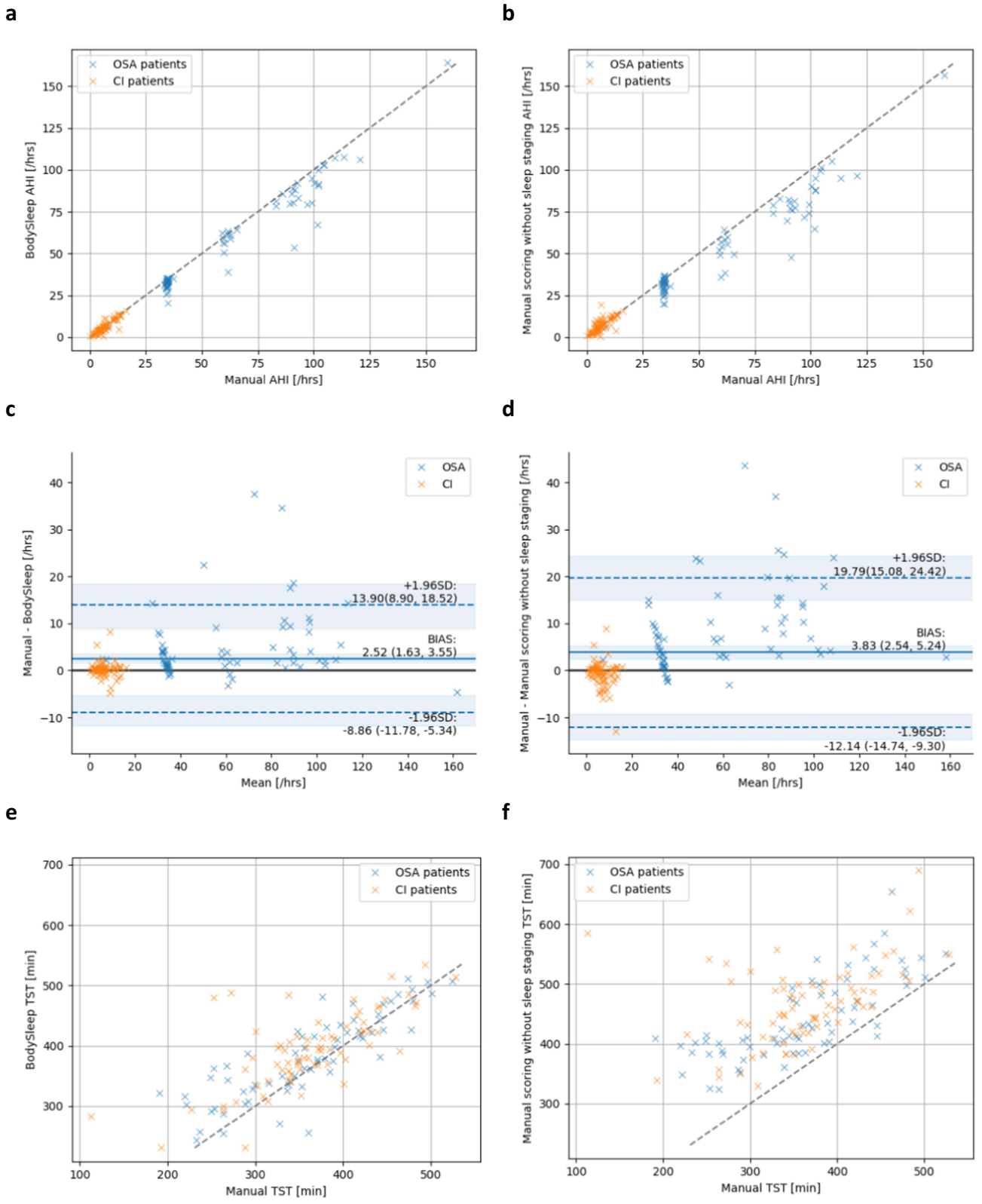
Agreement Between the Two Methods

Figure 2 shows the (a) scatter- and (c) Bland-Altman plot of AHI from manually scored recordings vs AHI from recordings scored with Nox BodySleep for OSA and CI patients, respectively. ICC between the two methods was 0.96 (95% CI 0.92–0.98) for OSA and 0.90 (95% CI 0.80–0.97) for CI patients, respectively.

Table 9 and Figure 2b and d show the same comparison when no sleep scoring is performed. The Bland-Altman plots showed (Figure 2c and d) that the bias and limits of agreement in the AHI were reduced when the Nox BodySleep was used compared to when no sleep scoring was performed.

Figure 2 shows the (e) scatter- and the (g) Bland-Altman plot of TST from manually scored recordings vs TST from recordings scored with Nox BodySleep for OSA and CI patients, respectively. ICC between the two methods was 0.80 (95% CI 0.71–0.87) for OSA and 0.64 (95% CI 0.43–0.80) for CI patients, respectively. When no sleep scoring was used, the ICC for the two groups were 0.46 (95% CI 0.37–0.54) for OSA and 0.21 (95% CI 0.04–0.38) for the CI patients.

Figures 2g and h show the Bland-Altman plots for the TST from the manual scoring vs Nox BodySleep, and manual scoring vs no sleep stages scored. The figures show that the bias is reduced from −93.34 (95% CI −104.46, −83.08) minutes when no sleep scoring is performed to −26.89 (95% CI −34.95, −19.16) minutes when the Nox BodySleep is



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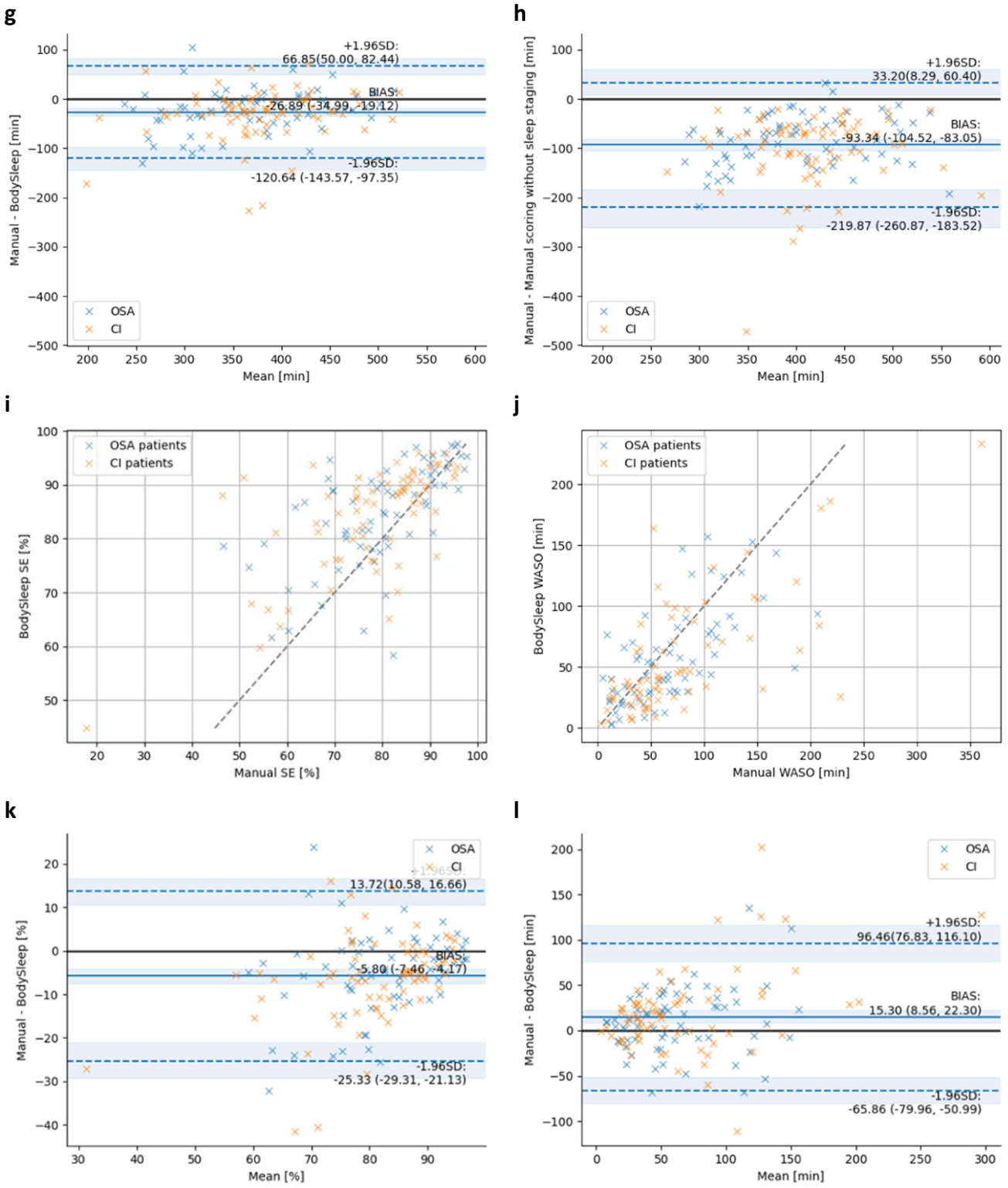

Figure 2 Scatter plots and Bland-Altman plots for the indices. The indices from the Nox BodySleepTM 1.0 and Manual scoring with no sleep scoring were compared against the manual scoring of polysomnography (PSG). (**a**–**d**): Apnea-Hypopnea Index (AHI), and (**e**–**h**): Total Sleep Time (TST). Sleep Efficiency (SE) and Wake after Sleep Onset (WASO) scatter plots (**i** and **j**) and Bland-Altman plots (**k** and **l**) from manually scored recordings vs recordings scored with the Nox BodySleep 1.0 algorithm, in both groups of patients with Obstructive Sleep Apnea (OSA) and with chronic insomnia.

Table 8 The Median Pairwise Difference Between the Absolute Error of Manual PSG Scoring Vs Nox BodySleep and the Absolute Error of Manual PSG Vs Manual Without Sleep Staging

	All (N=139)	OSA (N=67)	CI (N=72)
AHI [1/hrs]	−0.80 (−1.40, −0.60)	−2.20 (−3.40, −1.50)	−0.40 (−0.60, −0.20)
TST [min]	−46.10 (−50.70, −39.50)	−39.20 (−51.00, −29.20)	−48.45 (−55.25, −42.10)

Table 9 Intraclass Correlation Between Parameters Inferred from Nox's BodySleep Scorings versus the Parameters Calculated from Manual PSG Scorings for Each Cohort Alongside Bootstrapped 95% Confidence Intervals

	Nox BodySleep vs Manual PSG Sleep Staging			Manual PSG Scorings Without Sleep Staging vs Manual PSG Scorings with Sleep Staging		
	OSA Patients (N=67)	CI Patients (N=72)	Both Patient Groups (N=139)	OSA Patients (N=67)	CI Patients (N=72)	Both Patient Groups (N=139)
AHI	0.96 (0.92, 0.98)	0.90 (0.80, 0.97)	0.98 (0.97, 0.99)	0.92 (0.86, 0.95)	0.73 (0.56, 0.87)	0.96 (0.94, 0.98)
TST	0.80 (0.71, 0.87)	0.64 (0.43, 0.80)	0.72 (0.61, 0.81)	0.46 (0.37, 0.54)	0.21 (0.04, 0.38)	0.32 (0.20, 0.43)
SE	0.53 (0.38, 0.68)	0.56 (0.29, 0.73)	0.55 (0.39, 0.67)	–	–	–
WASO	0.62 (0.47, 0.76)	0.63 (0.38, 0.79)	0.63 (0.46, 0.75)	–	–	–

Notes: The intraclass correlation between manual scorings without sleep staging and with PSG sleep staging is included in the table for comparison.

used. Furthermore, Table 8 shows that the median pairwise error was reduced by −48.45 (95% CI −55.25, 42.10) minutes when the Nox BodySleep was used compared to when no sleep scoring was performed.

Figure 2 shows the (i) scatter plot and the (k) Bland-Altman plot of SE from manually scored recordings vs SE from recordings scored with Nox BodySleep for OSA and CI patients. Intraclass correlation (IC (2,1) between the two methods was 0.53 (95 CI 0.38–0.68) for OSA and 0.56 (95% CI 0.29–0.73) for CI patients.

Figure 2 shows the (j) scatter plot and the Bland-Altman plot of WASO from manually scored recordings vs WASO from recordings scored with Nox BodySleep for OSA and CI patients. ICC (2,1) between the two methods was 0.62 (95% CI 0.47–0.76) for OSA patients, and 0.63 (95% CI 0.38–0.79) for CI patients, respectively.

Discussion

As clinicians and researchers, we understand how important physiological signals are for the diagnosis of sleep disorders. We also acknowledge that beyond the simple visual classification of events, more information can be obtained on the patient's sleep by using spectral analysis, rapid eye movements, and sleep spindles.[7] Airflow is an essential criterion in the definition of sleep apnea. However, facing the COVID-19 pandemic and our inability to easily conduct PSG tests in sleep labs, we tried to determine if we could use signals mainly used before our study for HSAT purposes to diagnose OSA and insomnia with an algorithm based only on actigraphy (movements or no movement) and RIP belts. These are usually considered as limited signals that usually only assess respiratory rate variability, abdomen and thorax contributions to breathing, airflow rate and tidal volume of the lungs.

Recently, numerous studies have focused on the detection of sleep apnea assisted by machine learning, based on breathing sounds,[13,14] ECG and respiratory effort,[15] oximetry and airflow,[15] and heart-rate variability and airflow parameters.[16] Mostafa et al presented a recent review of 21 study devoted to the topic and concluded that ECG as a single source sensor allows an impressive global classification of states versus the other single signals.[17] However, SpO_2 signals seem to be the best single sensor for classification. Obviously, using more than one signal improves the predictive capability. In a previous work using the Nox BodySleep 1.0 algorithm for the first time, Dietz-Terjung et al compared the performance of the algorithm with manual scoring in a group of 127 patients with OSA.[8] They found that the method correlated strongly with a Pearson correlation coefficient (r) of 0.91 with a bias of 0.2/h for AHI estimation.

They found a weaker correlation (r = 0.81) and an overestimation of 14 min for TST. Regarding sleep states, they found a sensitivity of 0.65 and a specificity of 0.59. The sensitivity of Nox BodySleep for detecting REM and non-REM (NREM) states was 0.72 and 0.74, respectively, while specificity was 0.74 for NREM, and 0.68 for REM.

To our knowledge, the Nox BodySleep algorithm is the only available diagnostic tool for the detection of sleep states based on RIP technology and actigraphy. The application of this method has potential benefits to aid in the diagnosis of OSA in situations like the recent COVID-19 pandemic, when PSG studies were not feasible.

An important result of our study is the high level of agreement between sleep states derived from the Nox BodySleep algorithm and manually scored data. Considering the results presented in Table 2, the overall agreement score for detecting REM states epochs was 0.91 (95% CI 0.90, 0.92) and for wake states 0.87 (0.86, 0.89). We are aware that several studies have tried to evaluate sleep stages in patients with OSA based on heart rate variability, body movements and airflow.[18,19] We also have, with other authors, used EEG signals to estimate sleep states in patients with insomnia.[7,11,20,21] However, to our knowledge, this is the first time that sleep states were estimated via an algorithm, based only on RIP belts and actigraphy in patients with CI.

The technological advancement of using actigraphy and RIP belt signals processed by an AI algorithm may have important clinical consequences on the facilitation of the diagnosis of insomnia patients suffering from OSA. It is indeed well documented that insomnia is frequently associated with OSA, both before and after treatment. Before the diagnosis of insomnia, it has been demonstrated that respiratory events promote sleep awakenings that are associated with poor sleep and complaints of failure to maintain sleep. While treated with nasal continuous positive airway pressure (CPAP), some patients complain of sleep initiation insomnia, associated with the difficulty of sleeping with a mask, uncomfortable sleep positions, and early awakenings. In a recent review devoted to comorbid insomnia and sleep apnea (COMISA), the authors explained how, compared to either insomnia or OSA alone, the co-occurrence of these conditions is associated with greater morbidity for patients, complex diagnostic decisions for clinicians, and reduced responsiveness to otherwise effective treatment approaches. Potential bi-directional causal relationships between the mechanisms and manifestations of insomnia and OSA could play an integral role in the development and management of COMISA.[21] In the context of COMISA, it is easy to hypothesize that simple tools like actigraphy and RIP with the help of the Nox BodySleep algorithm may be helpful to follow and assess treatment effectiveness in these difficult patients. However, as the intra-class correlation for TST was 0.64 (0.3–0.80), the discussion of insomnia diagnosis and follow-up should be stated with care.

Moreover, COMISA may have severe consequences in other respiratory diseases like chronic obstructive pulmonary disease (COPD). Both insomnia and OSA are prevalent in patients with COPD and are linked to increased susceptibility to acute exacerbation of chronic obstructive pulmonary disease (AECOPD). Recently authors showed how improper treatment of insomnia may increase the risk of adverse respiratory outcomes for patients with COPD, while effective CPAP treatment may reduce the risk of AECOPD and mortality in patients with overlap syndrome.[22] We believe it could be useful to test the Nox BodySleep algorithm in these patients, especially regarding the severity index of OSA.

Our study has several limitations. The number of patients was limited (139) from a single center and did not include patients with PLM. However, the strength of this study is the inclusion of OSA and CI patients. The results were encouraging regarding the evaluation of sleep states. Furthermore, the significant reduction in the error of AHI and TST is quite important. It is probably important to entrain much more deeply the machine learning of Nox to improve the detection of wake states. It will be of interest to evaluate the performance of the newly released version of the Nox BodySleep algorithm (version 1.2) in this context.

We also acknowledge that most of our patients had severe insomnia and that the results may have been different for a majority of patients with mild or moderate OSA.

Finally, we hypothesize that limiting the number of signals recorded in patients with sleep disorders may be proposed in some scenarios, including during long-term patient follow-up, or when it is difficult to access the more comprehensive PSG data set for economic reasons or during an epidemic. However, having data from a complete PSG study including respiratory signals provides crucial information from a clinical perspective. Introducing AI tools like Nox BodySleep, as an alternative to a complete PSG system would also be an important step towards improving follow-up of a growing number of patients with multiple comorbidities. Concurrently, sleep clinicians and scientists must develop best practices

to integrate this rapidly evolving technology into sleep labs while maintaining the highest degree of quality and transparency in health care and research.[22] As stated by Watson & Fernandez:[23]

> The development of AI has the potential to transform sleep medicine in coming years to the betterment of patient care and our collective understanding of human sleep.

To conclude: the strength of our study was to identify an excellent AI algorithm, based on classic but limited signals used for HSAT and PSG, the activity and RIP belt signals, without airflow, which retrospectively identified sleep states, TST and OSA severity, not only in patients with OSA but also in patients with CI. The weaknesses of the study are the monocentric setting and the limited number of patients.

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Author Contributions

Damien Leger and Maxime Elbaz both made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

The authors declare no competing interest in this work.

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