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ORIGINAL RESEARCH

Utilizing a Wireless Radar Framework in Combination With Deep Learning Approaches to Evaluate Obstructive Sleep Apnea Severity in Home-Setting Environments

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Objective: Common examinations for diagnosing obstructive sleep apnea (OSA) are polysomnography (PSG) and home sleep apnea testing (HSAT). However, both PSG and HSAT require that sensors be attached to a subject, which may disturb their sleep and affect the results. Hence, in this study, we aimed to verify a wireless radar framework combined with deep learning techniques to screen for the risk of OSA in home-based environments.

Methods: This study prospectively collected home-based sleep parameters from 80 participants over 147 nights using both HSAT and a 24-GHz wireless radar framework. The proposed framework, using hybrid models (ie, deep neural decision trees), identified respiratory events by analyzing continuous-wave signals indicative of breathing patterns. Analyses were performed to examine correlations and agreement of the apnea-hypopnea index (AHI) with results obtained through HSAT and the radar-based respiratory disturbance index based on the time in bed from HSAT ($bRDI_{TIB}$). Additionally, Youden's index was used to establish cutoff thresholds for the $bRDI_{TIB}$, followed by multiclass classification and outcome comparisons.

Results: A strong correlation ($\rho = 0.87$) and high agreement (93.88% within the 95% confidence interval; 138/147) between the AHI and $bRDI_{TIB}$ were identified. The moderate-to-severe OSA model achieved 83.67% accuracy (with a $bRDI_{TIB}$ cutoff of 21.19 events/h), and the severe OSA model demonstrated 93.21% accuracy (with a $bRDI_{TIB}$ cutoff of 28.14 events/h). The average accuracy of multiclass classification using these thresholds was 78.23%.

Conclusion: The proposed framework, with its cutoff thresholds, has the potential to be applied in home settings as a surrogate for HSAT, offering acceptable accuracy in screening for OSA without the interference of attached sensors. However, further optimization and verification of the radar-based total sleep time function are necessary for independent application.

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Introduction

Obstructive sleep apnea (OSA) is a common sleep disorder characterized by repeated episodes of partial or complete obstruction of the upper airway during sleep, leading to a reduction in or complete cessation of airflow.[1] Globally, OSA is recognized as a significant public health issue, affecting an estimated 1 billion individuals aged 30–65 years, with approximately 425 million experiencing moderate-to-severe forms of the condition.[2] This disorder has been associated with a variety of comorbidities, including increased risks of cognitive decline, metabolic syndrome, and even acute myocardial infarction.[3,4] Hence, the importance of early diagnosis and prompt treatment cannot be overstated, as these measures are vital for the effective management of OSA.

In-laboratory polysomnography (PSG) is widely regarded as the gold standard for diagnosing OSA. This comprehensive test monitors various physiological parameters during sleep, such as brain activity, eye movement, muscle tone, heart rate, and breathing patterns.[5] Clinically, PSG is used to determine the apnea-hypopnea index (AHI) by scoring respiratory events, including apnea and hypopnea, and dividing the total number of these events by the total sleep time to assess the severity of OSA.[6] However, this examination requires an overnight stay in a sleep laboratory, which can be inconvenient due to excessive waiting times and may be costly for patients.[7] The first-night effects or the complex equipment of in-laboratory PSG may also affect the accuracy of the diagnosis due to the unfamiliar sleep environment or limited sleep positions in the hospital.[8,9] As a result, home sleep apnea testing (HSAT) has been proposed as a more-accessible and cost-effective alternative for diagnosing OSA, allowing patients to undergo testing in a home-based setting while still providing acceptable assessments of OSA.[10] However, even with HSAT, which uses fewer channels, patients who are easily awakened by attached sensors or cables may still experience effects on their sleep examination outcomes.[11] Developing wireless techniques is essential to mitigate the interference caused by hardware during sleep examinations.

To avoid disruptions from sleep testing equipment, it may be worthwhile to utilize contactless approaches. Prior research employed video or images collected by infrared cameras and motion sensors to develop models to identify respiratory events (ie apnea or hypopnea) during sleep.[12] Nonetheless, these wireless models are still in their early development phases and face various limitations. Specifically, factors such as the quality of the image data and impacts of minor movements, like eye blinking, can affect the accuracy of the results. Another study proposed a novel algorithm to predict the risk of having OSA via three-dimensional (3D) facial photographs; however, certain facial characteristics (eg, beards), may partially limit its further application.[13] Other studies extensively explored using wireless radar frameworks, such as ultra-wideband and Doppler radar, to detect respiratory events during sleep, highlighting their potential applications.[14,15] However, those proposed approaches predominantly rely on ultra-wideband frequency, which can be relatively expensive and require extensive hardware for radar signal transmission and reception. For example, an analysis of the features and costs of different radar-based techniques indicated that continuous-wave radar is more appropriate for practical use due to its cost-efficiency and sufficient accuracy in detecting human physiological movements.[16] A relevant study demonstrated the possibility of automated detection of apnea-hypopnea events for OSA diagnoses using a continuous-wave radar framework (60 GHz frequency-modulated) combined with convolutional recurrent neural networks by comparing the estimated results with PSG observations from 44 participants.[17] Their findings showed strong correlations (Pearson correlation ρ=0.81–0.95) and acceptable agreement (intraclass correlation ρ=0.78–0.93) between the estimates and ground-truth AHI values. Although previous results demonstrated the feasibility of using contactless radar as a surrogate for PSG in identifying OSA severity, those studies were primarily conducted in hospital-based settings and have not been validated in home-based environments. Therefore, further investigations with a more-diverse distribution of OSA severity are required to validate the wireless radar framework for sleep monitoring and clarify its feasibility in home-based environments.

In this prospective study, we explored the feasibility of using a wireless framework (with continuous-wave radar modules) combined with deep learning techniques to evaluate OSA severity in home-based settings. The hypothesis was

that radar-derived signals could capture respiratory patterns linked to sleep-disordered breathing, and analyzing these signals with trained deep-learning approaches could assist in evaluating OSA severity. We enlisted a cohort of 80 participants in northern Taiwan, recorded 147 nights of home-based sleep parameters as determined by HSAT and the proposed radar framework, and compared them. Additionally, cutoff thresholds for the proposed radar framework were established to screen for various levels of OSA severity. Findings of the present study demonstrated the feasibility of using a novel wireless radar-based sleep monitoring framework to provide accurate and reliable examination outcomes in home-setting environments.

Materials and Methods

Research Ethics and Protocols

The device specifications and safety certifications of the utilized radar framework (home-based sleep monitoring type) were submitted to the ethics committee for assessment. The research protocol received ethical approval from the Institutional Review Board at the Office of Human Research at a medical university in northern Taiwan (no. N202305074) and the relevant procedures complied with the *Declaration of Helsinki*. All recruited individuals were provided comprehensive information about the study and gave written informed consent before the research commenced. Data collection, processing, analysis, and maintenance were carried out following the approved protocols.

Participant Enrollment

This prospective study was conducted in northern Taiwan, with participants recruited by attending physicians at a sleep center in New Taipei City between January and September 2022. Patients who suspected themselves of snoring or were suspected of having OSA were invited to participate. Specifically, those who agreed to participate in the study were referred for continuous recording of sleep parameters for two to three nights in a home-based setting. The enrollment criteria were as follows: (1) being aged 20–75 years, (2) having no contraindications for HSAT, and (3) being able to independently operate the HSAT and set up the wireless radar framework after receiving comprehensive education.[18] As illustrated in Figure 1, the wireless radar framework was required to cover the upper body area within a distance ranging 75–90 cm. Next, participants were asked to wear the HSAT to measure sleep parameters. Since these two examinations were synchronized with internet time, the measurements obtained through the HSAT and wireless radar framework were automatically aligned based on the start time for further investigation.

Parameters of HSAT

In this prospective study, home-based sleep metrics were recorded using two established HSAT systems: ApneaLink (ResMed., San Diego, CA, USA) and Alice NightOne (Philips-Respironics, Murrysville, PA, USA). Both monitoring systems operate on battery power and have sensors to record signals that include nasal airflow, chest and abdominal movements, and pulse oximetry, with approximately 10 h of data collection possible.[19,20] ApneaLink (vers. 10.20) and Sleepware G3 (vers. 3.9.2) software were employed to automatically analyze the signals for each system, which were then manually reviewed again by certified technologists. Default settings for apnea and hypopnea events, as defined by the American Academy of Sleep Medicine, were pre-configured in both systems.[21] Specifically, an apneic episode was characterized by airflow reduction of 80% of the baseline for a minimum of 10s. A hypopneic episode involved an airflow decrease to 50–80% of the baseline for at least 10s. For the derived sleep outcomes, the total number of respiratory events, including the apnea index (AI), hypopnea index (HI), and their combined measure, namely the apnea-hypopnea index (AHI), were calculated based on the total in-bed time. The oximetry and pulse metrics, including the oxygen desaturation index (ODI), mean oxygen saturation (mean SpO_2), and mean, maximum, and minimum pulse, were obtained. The severity of OSA in the present study was categorized as normal (AHI < 5 events/h), mild (AHI of 5–15 events/h), moderate (AHI of 15–30 events/h), or severe (AHI of ≥ 30 events/h).[22]

Wireless Radar Framework and the Derived Index

This study utilized wireless radar sleep monitoring devices that had obtained safety certification in the motion-detection wireless category from the Taiwan National Communications Commission (CCAF19LP2510T5) and had received

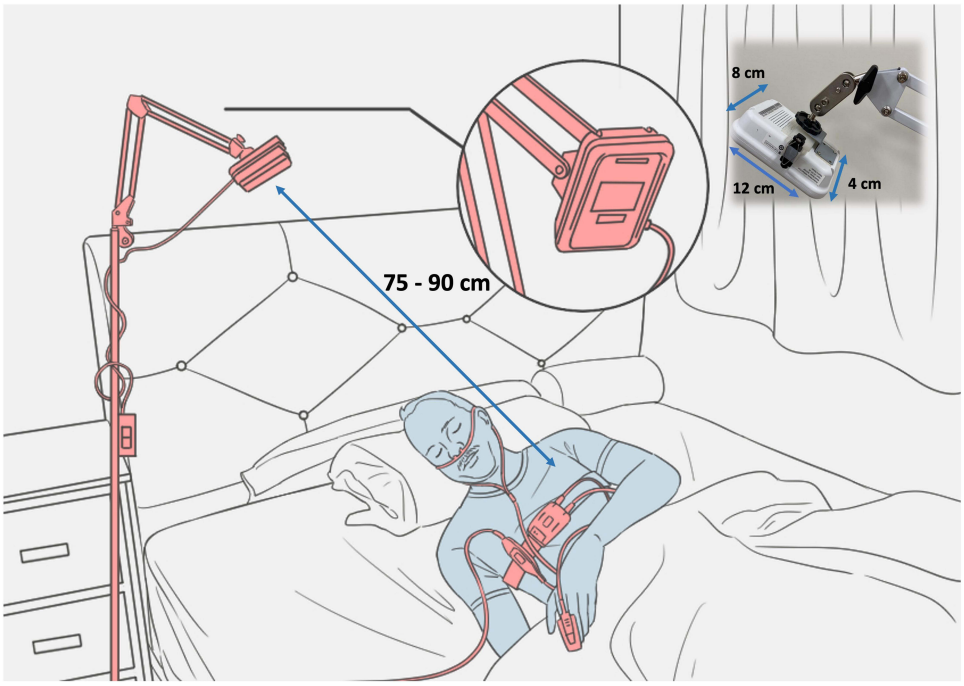

Figure 1 Size of the wireless radar framework and the installation illustration in a home-setting environment during home sleep apnea testing. Physiological signals were collected through home sleep testing equipment to calculate sleep parameters, and a wireless radar framework was simultaneously used to capture continuous-wave signals for monitoring breathing patterns. Notably, the utilized framework required the monitoring distance to range between 75 and 90 cm.

medical device approval for the non-contact monitoring system category from the Taiwan Ministry of Health and Welfare (license no. 007955). The device employs radio frequency modules to capture signals (24-GHz continuous-wave, with a wavelength of about 12.5 mm, to monitor chest wall movements). The primary reason for utilizing this specific frequency is that chest displacement caused by respiration and cardiac activity typically ranges 1–12 and 0.1–0.5 mm, respectively. When a subject is positioned 1–1.5 m from the device, the 24-GHz radar represents the optimal frequency band for clinically measuring physiological signals. Subsequently, the detected signals are analyzed through deep neural decision trees, hybrid models that integrate machine learning and deep learning features to predict respiratory events, and then the radar-based respiratory disturbance index (bRDI) was calculated. More technically, the deep neural decision tree consists of a neural network with a depth of 11 (with 4–10 neural nodes per layer), concatenated with a single decision tree to generate the final model output. Hyperparameters for these binary classification models were set as follows: a learning rate of 0.05, a batch size of 400, 200 training epochs, and a feature usage rate of 0.5.[23,24] After model generalization, the models were trained and validated to optimize model weights for event classification (ie, as a respiratory event or normal breathing) on a dataset of 29,496 instances (each lasting 30s). This dataset included both apneic and hypopneic events (N = 15,264) and normal respiratory data with no events (N = 14,232), collected from approximately 100 participants (male-to-female ratio: 3:2) across various sleep positions. Figure 2 presents the sensed signal waveforms of normal breathing and various respiratory events captured via HSAT and the wireless radar framework. Notably, the utilized wireless framework was validated by comparing the predicted bRDI and AHI from in-laboratory PSG.[25] In more technical details regarding the application in practical scenarios, the radar devices emitted radio frequency signals toward a participant lying in bed and detected the reflected signals. These signals underwent entropy calculations to detect patterns like peak-to-peak intervals, valley-to-valley intervals, and wave peak magnitudes, providing approximate respiratory patterns, which were then processed through a hybrid model to estimate the total abnormal breathing events to calculate the bRDI. Additionally, this device framework facilitated determination of the total sleep time by identifying distinct sleep stages, including wakefulness, rapid-eye-movement (REM), and non-REM (NREM) sleep, based on a similar structure of the aforementioned model (ie, with a neural network depth of 13). The development of this function underwent training and validation using a dataset comprising wake (N = 9833), NREM (N =

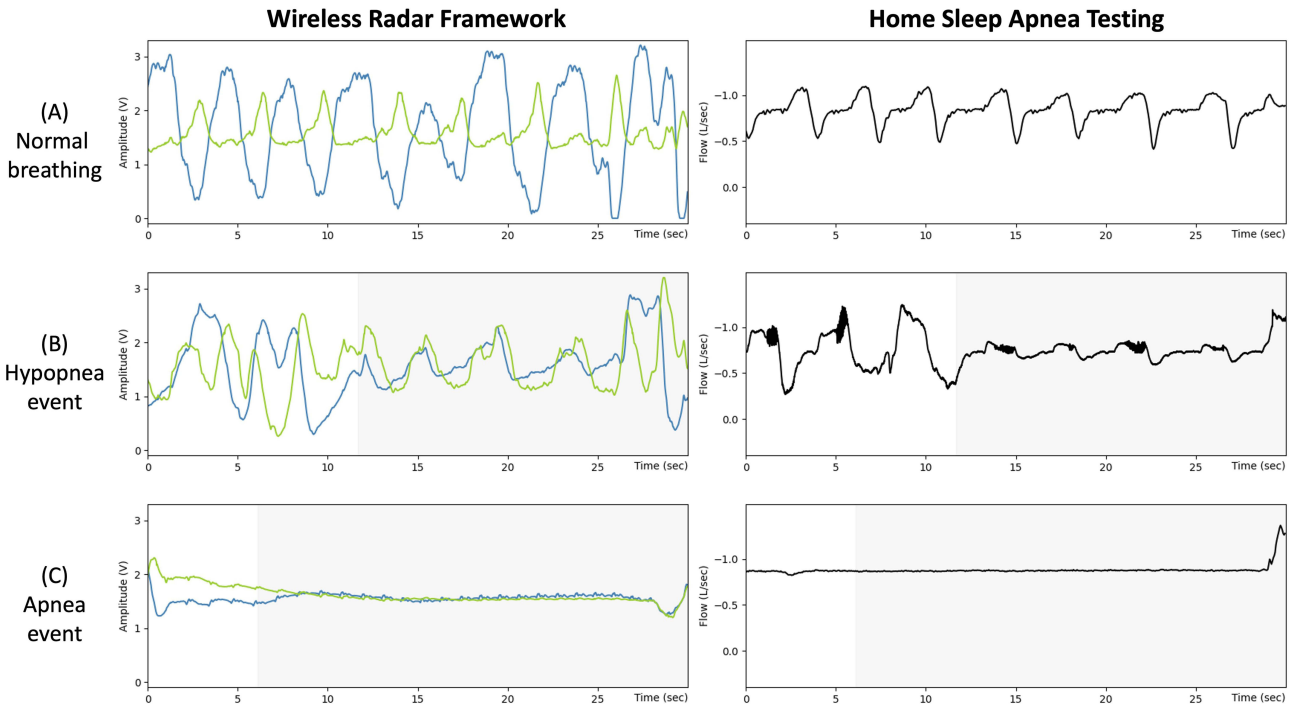

Figure 2 Signal waveforms of normal breathing patterns and those during hypopneic and apneic events captured using a wireless radar framework (Andar) and home sleep apnea testing (HSAT). The waveform signals from HSAT and the wireless radar framework illustrate different breathing patterns. Subpart (**A**) shows normal breathing, where both frameworks display regular and consistent waveforms corresponding to typical respiration. In subpart (**B**), a hypopnea event is depicted, characterized by a reduction in the waveform amplitude, indicating partial airway obstruction. Finally, subpart (**C**) represents an apneic event, with flattened waveforms demonstrating the absence of airflow due to complete airway obstruction.

11,503), and REM (N = 8160) stages, collected from the same subjects as the respiratory data. Figure S1 illustrates a comparison of sleep stages classified by the radar system with those determined by in-laboratory PSG.

Notably, the current research primarily focused on investigating application of a wireless radar framework. Therefore, in this study, the bRDI calculated based on the time in bed derived by HSAT ($bRDI_{TIB}$) was mainly used for comparison with the AHI from HSAT to align with the same time intervals. Regarding comprehensive information on specifications, installation procedures, and usage precautions for the device (such as warnings about signal errors), refer to prior research, which validated this wireless framework against in-laboratory PSG, demonstrating the accuracy of its derived parameters compared to hospital-based AHI.[25]

Statistical Analysis

Statistical analyses in this study were conducted using Scikit-learn (vers. 0.21.2), an open-source statistics library implemented in Python.[26] Baseline characteristics of enrolled individuals and indices from HSAT and the wireless radar framework were expressed as the mean with the standard deviation (SD). To investigate the relationship between the AHI (HSAT-based) and bRDI (radar-based), a Pearson correlation analysis was conducted with a significance threshold of $p < 0.05$. A Bland-Altman plot, a graphical method for comparing two quantitative measurements, was used to evaluate agreement between HSAT and the wireless radar framework.[27] The plot displays the difference between data points against the average of each pair on the x- and y-axes. The mean difference is represented by a horizontal line, while the upper and lower limits of agreement are calculated as the mean difference ± 1.96 times the SD of the differences. These limits were used to identify systematic bias between the two examinations and evaluate the degree of agreement.[28] Additionally, this study investigated the correlation and agreement among severe OSA data, which are presented in Figure S1.

Next, based on clinical guidelines and practical experience, active treatment was advised for patients with moderate-to-severe OSA (AHI ≥ 15 events/h),[29] while a curative intervention was strongly recommended for patients with severe

OSA (AHI ≥ 30 events/h).[30] Consequently, this study investigated the classification ability of the wireless radar device to differentiate these aforementioned three severity risks, specifically general OSA risk (AHI ≥ 5 events/h vs AHI < 5 events/h), moderate-to-severe OSA (AHI ≥ 15 events/h vs AHI < 15 events/h), and severe OSA (AHI ≥ 30 events/h vs AHI < 30 events/h).[31] Initially, the performances of both devices were compared utilizing the three cutoff thresholds of HSAT-based AHI (ie, ≥ 5, ≥ 15, and ≥ 30 events/h). Following this, a receiver operating characteristic (ROC) curve analysis was used to identify optimal bRDI cutoff thresholds based on Youden's index.[32] These derived cutoff thresholds were employed to separately classify general OSA, moderate-to-severe OSA, and severe OSA, and the area under the ROC (AUROC) was used to evaluate the performance of the established models. Additionally, the study evaluated and compared multiclassification performances (normal, mild, moderate, and severe OSA) using both cutoff thresholds of the AHI (HSAT-based) and bRDI (radar-based).

Results

Demographic Characteristics and Sleep Metrics

Table 1 presents demographic characteristics, sleep metrics (HSAT-based), and radar-based indices of the 80 enrolled participants. There were 66 males, forming the majority of participants, and 14 females, with an overall mean age of 48.05 (SD = 11.43) years. Regarding the home-based sleep metric summary across 147 days of recording, the mean time in bed was 370.29 (SD = 113.23) min. For the sleep disorder indices, which were calculated based on the time in bed, the mean AHI was 28.42 (SD = 29.52) events/h, and the ODI was 18.71 (SD = 16.78) events/h. For the radar-based index, the mean $bRDI_{TIB}$ was 26.89 (SD = 17.82) events/h, while the mean $bRDI_{pred}$ was 25.95 (SD = 17.33) events/h. For the determined OSA severity, 17.01% of the recordings were classified as normal (25 days), 30.61% as mild (45 days), 18.37% as moderate (27 days), and 34.01% as severe (50 days).

Correlations and Agreement Between HSAT and the Wireless Radar Framework

Figure 3 illustrates the correlation and agreement of the AHI derived from HSAT with the $bRDI_{TIB}$ obtained from the wireless radar framework. As depicted in Figure 3a, the two measures were significantly and highly correlated ($\rho = 0.87$, $p < 0.01$). The average difference between the HSAT-based AHI and radar-based $bRDI_{TIB}$ results was −5.3 (SD = 18.35)

Table 1 Demographic Characteristics and Home-Based Sleep Parameters of 80 Enrolled Individuals Across 147 days

Variable	Mean ± SD	Variable	Mean ± SD
Baseline characteristics		**Sleep disorder index*** (events/h)	
Age (years)	48.05 ± 11.36	AHI	28.42 ± 29.52
Sex (Male / Female)	66 / 14	AI	14.43 ± 14.3
BMI (kg/m^2)	25.69 ± 4.43	HI	13.99 ± 16.5
Waist girth (cm)	90.84 ± 10.96	ODI	18.71 ± 16.78
Neck girth (cm)	39.21 ± 4.0	Snoring index	69.18 ± 111.89
Home-based sleep summary		**OSA severity** (n, %)	
TIB (min)	370.29 ± 113.23	Normal	25 (17.01%)
Mean SpO_2 (%)	93.92 ± 1.71	Mild	45 (30.61%)
Mean pulse (bpm)	64.71 ± 9.13	Moderate	27 (18.37%)
Max pulse (bpm)	100.8 ± 26.06	Severe	50 (34.01%)
Min pulse (bpm)	52.55 ± 8.01		
Radar-based index* (events/h)			
$bRDI_{TIB}$	26.89 ± 17.82		
$bRDI_{pred}$	25.95 ± 17.33		

Notes: Data are expressed as mean ± standard deviation. *Indices were calculated based on the in-bed time.

Abbreviations: BMI, body mass index; TIB, time in bed; bpm, beats per minute; SpO_2, saturation of peripheral oxygen; $bRDI_{TIB}$, radar-based respiratory disturbance index (based on time in bed derived from home sleep apnea testing); $bRDI_{pred}$, radar-based respiratory disturbance index (based on the predicted total sleep time derived from radar); AHI, apnea-hypopnea index; AI, apnea index; HI, hypopnea index; ODI, oxygen desaturation index for ≥ 3%; OSA, obstructive sleep apnea.

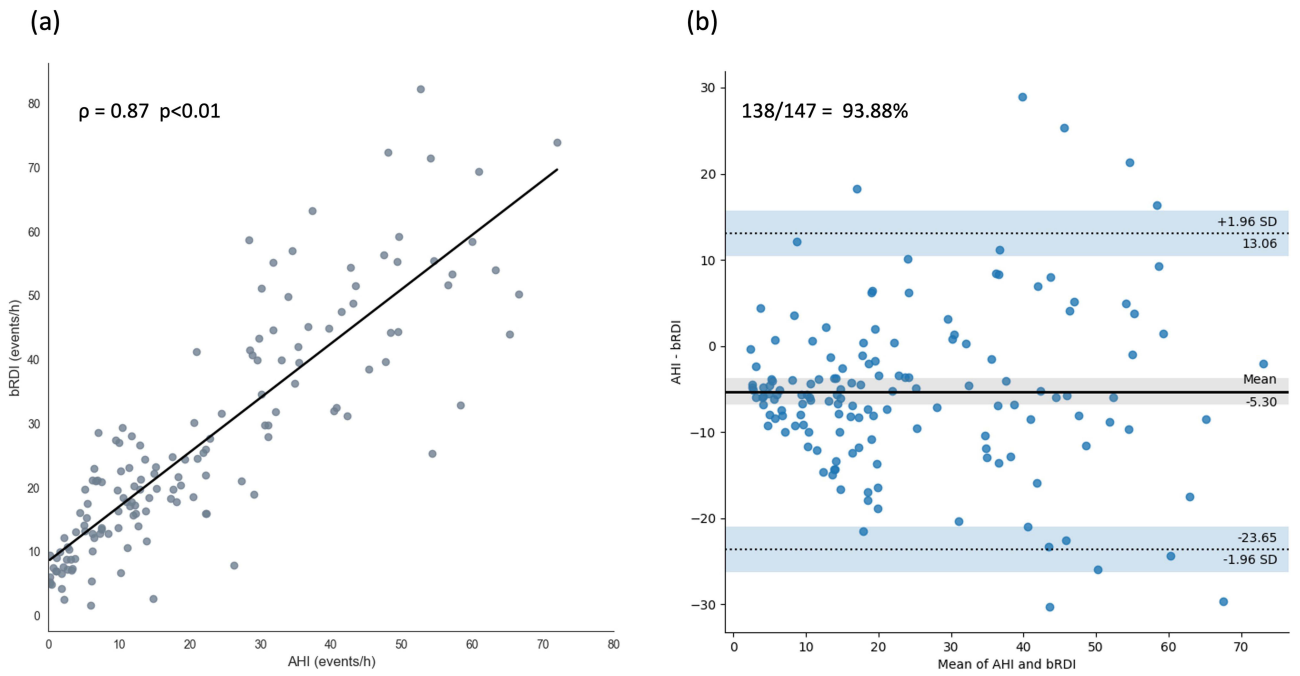

Figure 3 Correlation and Bland-Altman plots comparing the apnea-hypopnea index obtained from home sleep apnea testing (HSAT) with the radar-based respiratory disturbance index (bRDI) collected via a wireless radar framework (Andar). (**a**) Correlation between the apnea-hypopnea index (AHI) derived from HSAT and the respiratory disturbance index (bRDI) retrieved from the wireless radar framework. (**b**) Degree of agreement between results from HSAT (ie, AHI) and the wireless radar framework (ie, bRDI).

events/h (Figure 3b). The 95% confidence interval (CI) for the differences ranged −23.65 to 13.06 events/h, with 93.88% (138/147) of recorded days falling within this range. This study further analyzed the correlation and agreement among severe OSA data, which are presented in Figure S2. The correlation between the AHI and $bRDI_{TIB}$ remained significant ($\rho = 0.29$, $p < 0.05$). Regarding agreement, 92.0% (46/50) of the recorded days still fell within this range.

Binary Classification Outcomes of the Wireless Radar Framework Across Different Cutoff Thresholds

Table 2 illustrates the binary classification performance of the three severity models based on HSAT-derived AHI cutoff thresholds. For the general OSA model (AHI ≥ 5 events/h), the wireless radar framework with this cutoff threshold demonstrated an accuracy of 83.67% (SD = 5.98%) and an AUROC of 55.18% (SD = 8.04%). For the moderate-to-severe OSA model (AHI ≥ 15 events/h), the wireless radar framework with this cutoff threshold demonstrated an accuracy of 79.59% (SD = 6.52%) and an AUROC of 78.64% (SD = 6.63%). For the severe OSA model (AHI ≥ 30 events/h), the wireless radar framework with this cutoff threshold attained an accuracy of 92.52% (SD = 4.25%) and an AUROC of 91.42% (SD = 4.53%).

Using the corresponding cutoff thresholds derived from Youden's index for the wireless radar framework, Table 3 presents the classification performance of the three severity models. For the general OSA model, the cutoff threshold for the $bRDI_{TIB}$ was set to 12.91 events/h, which identified 112 days with values above this threshold. This model achieved an accuracy of 90.48% (SD = 4.75%) and an AUROC of 91.08% (SD = 4.61%). For the moderate-to-severe OSA model, the cutoff threshold for the $bRDI_{TIB}$ was set to 21.19 events/h, which identified 76 days with values that exceeded this threshold. This model achieved an accuracy of 83.67% (SD = 5.98%) and an AUROC of 83.71% (SD = 5.97%). Next, the severe OSA model utilized a cutoff threshold of 28.14 events/h for the $bRDI_{TIB}$, which identified 54 days with values above this level. The accuracy of this model was 93.21% (SD = 4.07%) with an AUROC of 92.95% (SD = 4.14%).

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Table 2 Classification Results for Identifying the Risk of Demonstrating Moderate-to-Severe and Severe Obstructive Sleep Apnea (OSA) Using a Wireless Radar System With Home Sleep Apnea Testing (HSAT) Severity Criteria (N = 80 With Data From 147 Days)

Variable	General OSA model	Moderate-to-severe OSA model	Severe OSA model
Cutoff* (events/h)	AHI: 5	AHI: 15	AHI: 30
N (≥ cutoff / < cutoff)	122 nights / 25 nights	77 nights / 70 nights	50 nights / 97 nights
Precision (%)	84.51 ± 5.85	72.38 ± 7.23	89.81 ± 4.89
Recall (%)	98.36 ± 2.05	98.71 ± 1.83	88.01 ± 5.25
Accuracy (%)	83.67 ± 5.98	79.59 ± 6.52	92.52 ± 4.25
F1-score (%)	90.91 ± 4.65	83.52 ± 6.0	88.89 ± 5.08
AUC (%)	55.18 ± 8.04	78.64 ± 6.63	91.42 ± 4.53

Notes: *According to clinical guidelines, the cutoff values are defined as follows: general OSA (AHI ≥ 5 events/h), moderate-to-severe OSA (AHI ≥ 15 events/h), and severe OSA (AHI ≥ 30 events/h). Data are expressed as the mean ± standard deviation.
Abbreviations: AHI, apnea-hypopnea index; AUC, area under the curve.

Table 3 Classification Results for Identifying the Risk of Demonstrating Moderate-to-Severe and Severe Obstructive Sleep Apnea (OSA) Using a Wireless Radar System With Retrieved Cutoff Thresholds (N = 80 With Data From 147 Days)

Variable	General OSA Model	Moderate-to-severe OSA Model	Severe OSA Model
Cutoff* (events/h)	bRDI: 12.91	bRDI: 21.19	bRDI: 28.14
N (≥ cutoff / < cutoff)	112 nights / 35 nights	76 nights / 71 nights	54 nights / 93 nights
Precision (%)	98.21 ± 2.14	85.33 ± 5.72	88.68 ± 5.12
Recall (%)	90.16 ± 4.81	83.12 ± 6.06	92.16 ± 4.35
Accuracy (%)	90.48 ± 4.75	83.67 ± 5.98	93.21 ± 4.07
F1-score (%)	94.02 ± 3.83	84.21 ± 5.89	90.38 ± 4.77
AUC (%)	91.08 ± 4.61	83.71 ± 5.97	92.95 ± 4.14

Notes: *According to the Youden index. Data are expressed as the mean ± standard deviation.
Abbreviations: bRDI, radar-based respiratory disturbance index; AUC, area under the curve.

Multiclass Classification Outcomes of the Wireless Radar Framework Across Different Cutoff Thresholds

Regarding the multiclass classification for specifically identifying risks of having normal, mild, moderate, and severe OSA, the present study employed three different thresholds. First, Table 4 illustrates multiclass classification performances based on HSAT-derived AHI cutoff thresholds (ie, of 5, 15, and 30 events/h). An overall accuracy of 56.46%, an average recall of 52.78%, and a precision of 56.96% were obtained from the established model. Subsequently, using corresponding cutoff thresholds derived from Youden's index for the wireless radar framework ($bRDI_{TIB}$ of 12.91, 21.19,

Table 4 Classification Results for Identifying the Risk of Demonstrating Normal, Mild, Moderate or Severe Obstructive Sleep Apnea Using a Wireless Radar System With Home Sleep Apnea Testing (HSAT) Severity Criteria (N = 80 With Data From 147 Days)

HSAT	Wireless Radar Sleep Monitoring Device (Andar)				Recall (%)
	Normal	Mild	Moderate	Severe	
Normal	3	21	1	0	12.0%
Mild	2	15	28	0	33.33%
Moderate	0	1	21	5	77.78%
Severe	0	0	6	44	88.0%
Precision (%)	60.0%	40.54%	37.51%	89.80%	56.46%

Abbreviation: HSAT, home sleep apnea testing.

Table 5 Classification Results for Identifying the Risk of Demonstrating Normal, Mild, Moderate or Severe Obstructive Sleep Apnea Using a Wireless Radar System With Retrieved Cutoff Thresholds (N = 80 With Data From 147 Days)

HSAT	Wireless Radar Sleep Monitoring Device (Andar)				Recall (%)
	Normal	Mild	Moderate	Severe	
Normal	23	2	0	0	92.0%
Mild	11	23	10	1	51.11%
Moderate	1	10	10	6	37.04%
Severe	0	2	2	46	92.0%
Precision (%)	65.71%	62.16%	45.45%	86.79%	69.39%

Abbreviation: HSAT, home sleep apnea testing.

and 28.14 events/h), Table 5 presents the classification performances. This model attained an overall accuracy of 69.39%, an average recall of 68.04%, and a precision of 65.03%.

Discussion

To assess the feasibility of employing a wireless radar framework in home-setting environments, in this prospective study, we collected sleep metrics from HSAT and the wireless radar framework and conducted comparisons. Based on the collected sleep dataset from 80 participants across 147 nights, this study validated the accuracy of the proposed wireless radar framework combined with deep learning techniques for screening OSA severity. Results showed a high measurement agreement compared to HSAT results. Additionally, derived cutoff thresholds for normal, moderate-to-severe, and severe OSA were separately established. These outcomes suggested that the proposed framework can be effectively applied in home-based sleep environments, offering the advantage of noncontact measurement to avoid the risk of interference with sleep results due to attached sensors or examination equipment.

Prior studies compared outcomes of various novel sleep monitoring devices to PSG or HSAT to evaluate their prediction performance. For example, researchers utilized a wearable device (patch-type) that integrated a single-lead electrocardiogram and a three-axis accelerometer to screen for OSA risk, achieving outcomes with AUROCs of 0.82 for the moderate-to-severe OSA model and 0.91 for the severe OSA model.[33] However, such a type of device is not recommended for individuals with atrial fibrillation, an implanted pacemaker, ventricular tachycardia, or pregnancy due to the difficulty of analyzing cardiac signals amidst excessive arrhythmias.[34] Since the approach of the present proposed framework wirelessly detects breathing patterns to identify respiratory events, it may be less susceptible to the effects on sleep caused by attached sensing devices.[35] In addition, as aforementioned, the proposed framework was validated against in-laboratory PSG, demonstrating high accuracies of 90.3% for the moderate-to-severe OSA model and 92.4% for the severe OSA mode.[25] Taken together, the present results elucidate application of the proposed wireless framework for identifying respiratory events, suggesting its suitability for OSA risk screening in home-based environments.

Regarding differences in wireless techniques and their respective advantages and disadvantages, high-frequency wireless methods provide greater resolution for detecting small movements but are limited by shorter ranges and sensitivities to obstructions like clothing. Conversely, low-frequency techniques, though less sensitive, penetrate materials more effectively and are suitable for detecting chest movements over short distances, such as in bed setups. Therefore, the trade-off between frequency and sensitivity must be carefully considered. The present study employed high-frequency wireless methods, specifically utilizing a 24-GHz continuous-wave radar framework with a wavelength of approximately 12.5 mm. Specifications of this type of radar are suitable for detecting typical respiratory- and heart rate-induced chest movements, which respectively normally range 1–12 and 0.1–0.5 mm.[36,37] Previously, researchers utilized this specific frequency range to detect signals, especially in the thoracic space. For example, one study employed a 24-GHz radar embedded as a medical device to detect cardiograms, and their results revealed a high accuracy of 98% in cardiac timing detection.[38] Similarly, another study employed 24–24.5-GHz frequency-modulated continuous-wave radar

to establish a vital sign monitoring system that demonstrated highly accurate measurements of respiratory and heart rates, validated based on both simulation and experimental datasets.[39] Altogether, when considering the costs and benefits of using an ultra-wideband method, the 24-GHz continuous-wave radar utilized in this study appears to be the optimal choice for measuring breathing patterns and chest wall movements, particularly when individuals are positioned approximately 1–1.5 m from the measurement device. However, in multiclass classification, the current outcomes demonstrated relatively low recall in distinguishing between normal and mild cases but showed adequate performance in moderate and severe classifications. This may be attributed to detection limitations of subtle chest wall movements caused by partial obstructions, which require further improvement. Additionally, obstructions like clothing or duvets may further impact respiratory event identification. Therefore, a more-comprehensive dataset, including patients with normal and mild OSA, is needed to enhance the performance of this wireless approach.

There are several strengths to the present study. First, building on our previous outcomes that focused on validating the accuracy of using the proposed radar framework as an alternative to in-laboratory PSG, this study further investigated the feasibility of employing such a system in a home setting and compared measurements with those from another routine home sleep examination (ie, HSAT).[25] The statistical findings demonstrated strong correlations between the AHI from HSAT and $bRDI_{TIB}$ from the wireless radar framework, along with a high concordance between these two approaches. This indicates that the proposed wireless approach could feasibly serve as a surrogate for HSAT and be further applied in home-based sleep environments. Next, this study demonstrated that using cutoff thresholds for moderate-to-severe OSA and severe OSA yielded classification results with satisfactory prediction accuracies and adequate AUROC values per the derived radar-based index. Additionally, the proposed system, which consisted solely of an ensemble radar device combined with deep learning models, enabled the automated estimation of reasonably accurate $bRDI_{TIB}$ results. Most importantly, due to their wireless nature, radar devices are suitable for individuals whose sleep behaviors may be easily disrupted by attached sensors or laboratory sleep environments, providing more accurate and representative sleep metrics. Additionally, the proposed framework does not require technician attendance and can be applied in a home-setting environment, allowing for continuous monitoring and result scoring. Hence, using this framework, outcomes of multi-day examinations can be obtained, enabling comprehensive data analysis to accurately and sensitively screen for OSA severity.

There are some limitations to the current study. First, most of the participants were male, which is a frequent constraint in sleep disorder research and may have introduced a gender bias. The present study only enrolled patients who had no contraindications for HSAT, which may have avoided effects due to underlying diseases or medications. However, other factors, such as individual upper airway anatomy and craniofacial factors, oral hygiene, and personal habits (eg, cigarette or caffeine usage), can still affect breathing patterns (eg, buccal respiration).[40,41] In addition, previous researchers proposed using 3D facial photographs to analyze craniofacial anatomy for predicting the risk of OSA and demonstrated approximately 90% accuracy.[13] These factors should be considered when utilizing the proposed wireless framework. Regarding comparisons of the sleep disorder index between HSAT and the wireless framework, outcomes of this study were mainly based on the time in bed derived from HSAT. Although the proposed framework enabled an estimate of the total sleep time utilizing the radar signal, the reliability of these functions requires further refinement and validation in future studies. Some studies proposed various machine learning approaches to classify sleep stages, which could be considered for further integration into the proposed wireless radar framework.[42,43] Additionally, compared to outcomes from HSAT, the proposed framework primarily focused on detecting respiratory events and was unable to present oximetry-related details due to its contactless nature. However, the absence of oximetry data may hinder the precise identification of oxygen desaturation conditions, which can assist in accurately determining respiratory events or even further classify other OSA phenotypes.[44,45] Hence, integrating oximetry data should be considered to more comprehensively evaluate OSA severity. Next, the current models were primarily designed to detect respiratory events (ie, apnea or hypopnea). However, they did not effectively distinguish between central and obstructive types of these events. Future work should consider improving the models to differentiate between central and obstructive event types by integrating additional physiological signals or advanced machine-learning techniques. Collectively, future studies should focus

on integrating pulse oximetry, verifying the sleep time estimation function, and distinguishing between different types of sleep apnea, such as central and obstructive sleep apnea. By conducting more independent trials for additional function validation, the proposed wireless framework may achieve enhanced robustness, generalizability, and accuracy compared to HSAT.

Conclusions

To explore the feasibility of using a wireless radar framework in a home setting, in this prospective study, we collected data from HSAT and a wireless radar framework, combined with deep learning methods to compare results. Across 147 days of sleep data from 80 participants, significant, high correlation ($\rho = 0.87$) and agreement (93.88%) between the AHI of HSAT and the $bRDI_{TIB}$ of the wireless radar framework were determined. Additionally, OSA severity classification models using AHI criteria (HSAT-based) or derived cutoff thresholds for the $bRDI_{TIB}$ (radar-based) were established, allowing for a comparison between binary and multiclassification performances in determining OSA severity. The mild-to-severe OSA models exhibited adequate accuracy with the AHI (79.59%) and $bRDI_{TIB}$ (83.67%). For the severe OSA models, high accuracy was achieved with both the AHI (92.52%) and $bRDI_{TIB}$ (93.21%). In the multiclassification models, the AHI-based model achieved 72.11% accuracy, while the model based on $bRDI_{TIB}$ achieved 78.23% accuracy. Altogether, the wireless radar framework combined with deep learning models (ie, a deep neural decision tree model) introduced in this study could be considered for application in home-setting environments as an alternative to HSAT for rapid OSA risk screening, offering the advantage of contactless monitoring. However, further research and optimization are necessary to refine and empirically validate the accuracy of this framework.

Highlights

- We proposed a wireless radar framework combined with deep learning techniques for screening OSA severity in home-based environments.
- The feasibility of employing a wireless radar framework for sleep monitoring in home-based environments was assessed.
- Specific cutoff thresholds for OSA (AHI $\geq$ 5 events/h), moderate-to-severe level (AHI $\geq$ 15 events/h), and severe level (AHI $\geq$ 30 events/h) using the radar framework were derived.
- Reliable accuracy and high measurement agreement between the proposed wireless system and HSAT were demonstrated.

Abbreviations

AHI, apnea-hypopnea index; AI, apnea index; AUROC, area under the receiver operating characteristic curve; AUC, area under the curve; ArI, arousal index; BMI, body-mass index; HI, hypopnea index; NREM, non-rapid eye movement; ODI, oxygen desaturation index for $\geq$ 3%; OSA, obstructive sleep apnea; PSG, polysomnography; RDI_{PSG_TST}, respiratory disturbance index obtained through radar device measurement and divided by the total sleep time determined by polysomnography; $RDI_{Radar\text{-}Based\_TST}$, respiratory disturbance index obtained through radar device measurement and divided by the total sleep time determined by the radar system; REM, rapid eye movement; SD, standard deviation; SpO_2, peripheral capillary oxygen saturation; TST, total sleep time; WASO, wake time after sleep onset.

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Disclosure

The authors declare no conflicts of interest in this work.

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