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# Detection of apnea and hypopnea events using a wireless Abdomen-Worn sensor with $SpO_2$ integration

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## Abstract

**Purpose** Polysomnography is the gold standard for diagnosing sleep apnea (SA), but it is costly and not widely available. Home sleep apnea testing (HSAT) offers a more accessible, lower-cost alternative. Type III HSAT typically uses nasal pressure sensors, respiratory inductance plethysmography (RIP) belts, and pulse oximetry; however, nasal sensors and RIP belts may be uncomfortable or unsuitable for some patients. This study assessed whether apnea and hypopnea events can be detected using a wireless abdomen-worn sensor (Soomirang) combined with $SpO_2$ monitoring, eliminating the need for nasal pressure sensors or RIP belts.

**Methods** Data from 37 participants were collected using the Soomirang device and a typical type III HSAT (AL). Two models were developed for apnea and hypopnea event detection: SoomOxy, combining abdominal and body movement data with $SpO_2$, and Soom, using abdominal and body movement data alone. Their performance was evaluated against AL.

**Results** SoomOxy demonstrated strong agreement with AL, achieving an area under the curve of 0.9447 for apnea and 0.8702 for hypopnea detection, a predicted apnea hypopnea index correlation of 0.96, and an average accuracy of 0.8286 across all severity categories. The SoomOxy outperformed Soom model in detecting hypopnea events.

**Conclusion** A wireless abdomen-worn sensor combined with $SpO_2$ monitoring can accurately detect and classify apnea and hypopnea events without nasal pressure and RIP belts, offering a practical and more comfortable alternative to conventional HSAT setups.

**Keywords** Sleep apnea · Abdomen-worn sensor · Apnea hypopnea detection · Wearable device · Home sleep apnea testing · $SpO_2$

## Introduction

Sleep apnea (SA) is a sleep disorder characterized by repeated episodes of reduced (hypopnea) or absent (apnea) airflow lasting at least 10 s, often accompanied by intermittent drops in blood oxygen saturation [1, 2]. SA is highly prevalent among patients with cardiovascular disease, affecting over 40% of this population, and contributes to worsening cardiovascular outcomes [3]. Despite its clinical significance, SA remains underdiagnosed and undertreated in routine cardiovascular care [4]. Polysomnography (PSG) is the gold standard for SA diagnosis, but is costly and not widely accessible [5]. Consequently, home sleep apnea testing (HSAT) has emerged as a practical alternative due to its lower cost, accessibility, and convenience [5, 6]. Various HSAT techniques have been developed utilizing a reduced set of physiological signals, including electrocardiography, airflow, breathing pattern, pulse oximetry, and snoring measurements [7–19].

According to the guidelines set by the American Academy of Sleep Medicine (AASM), a level III HSAT must record a minimum of four physiological signals: heart rate, oxygen saturation, and either two respiratory effort channels or one respiratory effort channel alongside airflow [5]. Most level III devices available on the market commonly assess airflow through nasal pressure sensors, paired with respiratory inductance plethysmography (RIP) belts and pulse

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oximetry. Airflow and $SpO_2$ signals are considered as the primary indicators for detecting apnea and hypopnea events [2, 5]. Numerous studies have reported high detection performance using this approach [7–9]. However, nasal pressure monitoring requires nasal cannulas or masks, which can be uncomfortable and inconvenient for some patients during sleep. In scenarios where airflow measurement is failed or difficult, such as in patients using supplemental oxygen or non-invasive ventilation masks, thoracoabdominal movement signals measured by RIP belts provide a practical alternative [2, 10–12].

Previous studies have shown that respiratory events can be identified without nasal pressure monitoring by relying solely on a RIP belt or wearable band combined with pulse oximetry, providing a viable alternative when nasal sensors fail in level III devices [13–15]. Although these approaches are effective for automatically detecting respiratory events, they did not attempt hypopnea detection, which is common in the SA population and linked to metabolic syndromes [20]. The detection of hypopnea is essential for clinical diagnosis and treatment planning. Moreover, the RIP belt can be uncomfortable, restrictive, and have higher power requirements [21].

Our previous work introduced a wireless abdomen-worn sensor (Soomirang) that measures both abdominal movement via capacitance and overall body movement through a three-axis accelerometer, providing a promising alternative for SA detection [22]. In this study, we investigate the feasibility of detecting apnea and hypopnea events using abdominal and body movement signals from this wireless sensor in combination with $SpO_2$ monitoring. This approach enables a detection system that does not rely on nasal pressure sensors and may also serve as an alternative to conventional RIP belts, offering a simpler and more comfortable option for both clinical testing and HSAT.

## Methods

### Data collection

A total of 37 adult participants were enrolled in this study after providing written informed consent. The study protocol received ethical approval from the Institutional Review Board of Ulsan National Institute of Science and Technology (UNISTIRB-24-006-A). Each participant underwent overnight sleep monitoring with concurrent data collection from two systems: the ApneaLink Air™ device (AL, ResMed, USA) and Soomirang (SB solutions, Ulsan, Republic of Korea). The AL device was selected due to its established reliability in SA detection and its broad adoption in HSAT [23, 24]. The AL device recorded airflow at a sampling rate of 100 Hz, thoracic respiratory effort at 10 Hz, and both pulse rate and $SpO_2$ at 1 Hz. Simultaneously, the Soomirang sensor was placed on the upper abdomen (between the navel and sternum) to record abdominal surface movement using fringing-field capacitive sensing and body movement via a three-axis accelerometer, both sampled at 5 Hz.

The capacitive sensing mechanism operates by detecting changes in the mutual capacitance (Cm) between electrodes, which vary according to the proximity of the body surface. As the abdomen expands during inhalation, the sensor moves closer to the skin, increasing Cm and decreasing the calculated capacitance variation (Cv = Co − Cm), where Co represents the baseline capacitance. During exhalation, the opposite occurs: abdominal contraction increases the distance from the sensor, reducing Cm and thus increasing Cv.

### Preprocessing

The datasets from the AL and Soomirang sensors were temporally aligned to ensure proper synchronization. Apnea and hypopnea events were annotated using the AL software (version 10.10). Each Soomirang data sample was labeled based on its temporal alignment with annotated events: if the sample's timestamp fell within the time window of an annotated apnea or hypopnea, it was labeled as 'apnea' or 'hypopnea', respectively. Samples whose timestamps did not overlap with any annotated events were labeled as 'non-apnea'. To match the sampling rate of the Soomirang data, the $SpO_2$ signal was upsampled from 1 to 5 Hz. The $SpO_2$ signals were shifted backward by 20 s to address the physiological delay between respiratory events and the resulting oxygen desaturation. Given that the median event duration in our dataset is 27.7 ± 15.66 s, this 20-second shift was selected to prevent excessive shifting for shorter events. Artifact removal was performed on the $SpO_2$ data by excluding values above 100% or below 50%, which were considered invalid. The capacitive and three-axis acceleration signals were processed following the method outlined in our previous study [22].

### Feature extraction

Eight features were extracted from the recorded signals: five features from the Soomirang sensor and three features from $SpO_2$. Features from the Soomirang sensor include cap, gap, pos, acc_length, and ratio_cap [22]. The cap was obtained by smoothing the capacitive signal using a Savitzky-Golay filter (window length: 11 samples, order: 3), followed by z-score normalization. The gap was computed as the max–min difference within a five-sample moving window of the cap to capture second-by-second variations. The pos was body position derived from gravitational acceleration and tilt angles, and classified into upright, supine, prone, left, and right [22]. The acc_length was calculated as the square root of the sum of squared values from the three-axis acceleration [22]. Moreover, we computed changes in abdominal movement amplitude over time (ratio_cap). At each time point in the cap signal, the ratio_cap was calculated as the ratio between the 95th percentile amplitude within a 5-second forward window and that of a backward window. A higher ratio indicates a rising trend in abdominal movement, while a lower ratio suggests a reduction, potentially reflecting breathing irregularities.

Features from $SpO_2$ include the normalized $SpO_2$, desaturation depth (depth_oxy), and the desaturation duration (dur_oxy). The normalized SpO2 was calculated by dividing each value of the valid $SpO_2$ by 100. The depth_oxy was calculated as the difference between the maximum and minimum within a 25-sample sliding window to capture local changes in the $SpO_2$ signal. The interval between these local extremes was measured as the desaturation duration (dur_oxy). Figure 1 presents example signals recorded by AL and Soomirang during periods featuring apnea and hypopnea events.

## Respiratory event detection

The MLP-Mixer architecture, previously proposed for time series analysis tasks, was employed in this study [22, 25]. It processes data using a sliding-window approach, where a 100-second window moves sequentially across the full sleep recording. Two multiclass classification models were developed to classify non-apnea, apnea, and hypopnea events. The first model (SoomOxy) used both Soomirang-derived features and $SpO_2$-based features as inputs: five features from Soomirang (cap, gap, acc_length, pos, and ratio_abd) and three from $SpO_2$ (normalized $SpO_2$, depth_oxy, and dur_oxy). The second model (Soom) used only the five Soomirang-derived features. A detailed evaluation of apnea and hypopnea detection performance using different feature groups for each model is provided in the online supplement. Both models were trained using subject-wise five-fold cross-validation with a batch size of 32, and a window length of 500 samples. The model consisted of two hidden layers, each with a hidden dimension of 32. Training was conducted for 100,000 iterations using the Adam optimizer with a learning rate of 0.0005. Figure 2 illustrates the overall framework for apnea/hypopnea event detection and SA severity classification using MLP-Mixer based models.

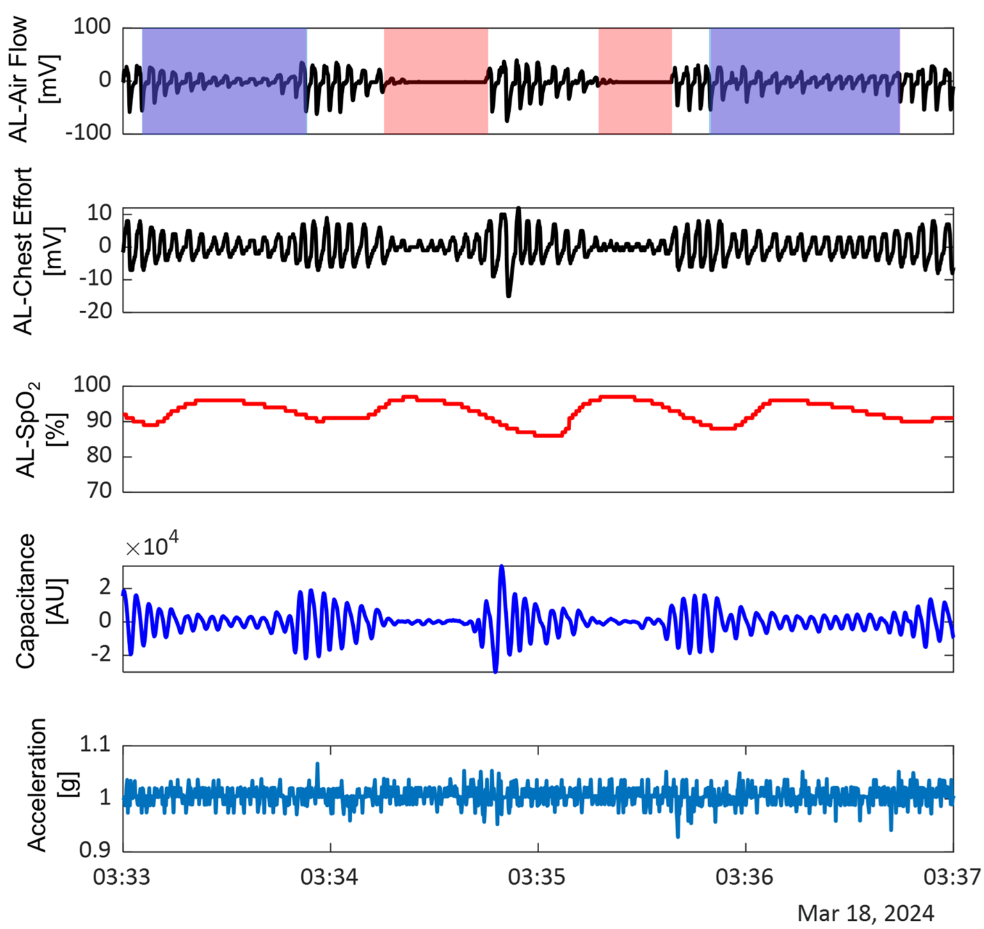



**Fig. 1** Example signals recorded by ApneaLink Air™ (AL) and Soomirang devices during periods featuring apnea (red area) and hypopnea (blue area) events. AL-Airflow, AL-ChestEffort, and AL-$SpO_2$ signals correspond to airflow, chest effort, and $SpO_2$ signals measured from AL. Capacitance and acceleration signals represent the capacitive signal and the length of acceleration calculated from a three-axis accelerometer, both obtained from Soomirang

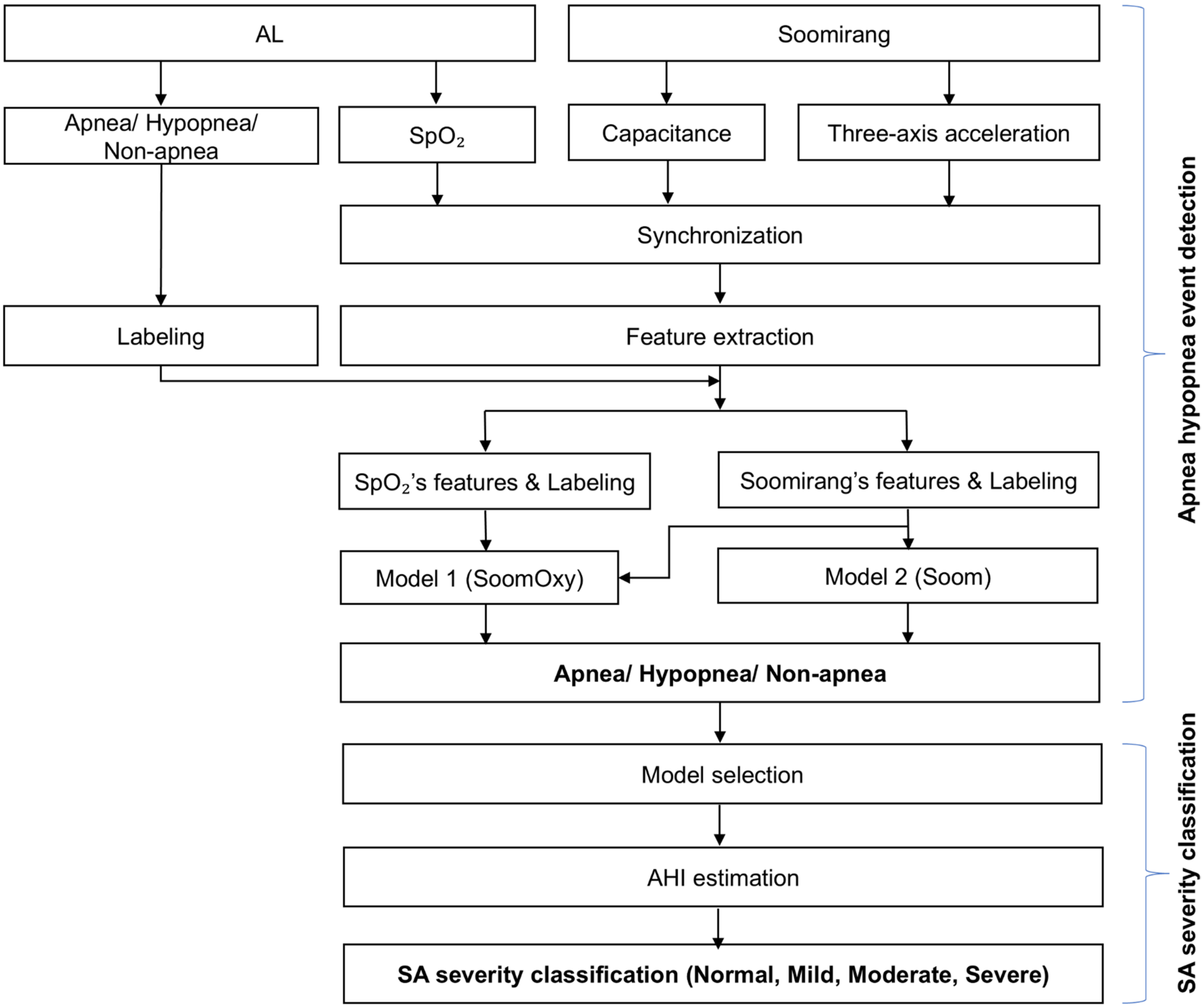



**Fig. 2** Overall framework for apnea/hypopnea event detection and sleep apnea (SA) severity classification using MLP-Mixer based models. Physiological signals were simultaneously acquired from the ApneaLink Air™ (AL) device and the Soomirang system. The AL system provided reference event labels (apnea, hypopnea, and non-apnea) along with $SpO_2$ signals, while the Soomirang sensor recorded capacitance and tri-axial acceleration signals. After synchronization of all signals, features were extracted separately from the Soomirang and $SpO_2$ data. Two models were developed for comparison: Model 1 (SoomOxy), utilizing both Soomirang-derived and $SpO_2$-based features, and Model 2 (Soom), utilizing only Soomirang-derived features. Both models were trained and evaluated using AL-derived labels corresponding to non-apnea, apnea, and hypopnea events. The detected apnea and hypopnea events from the selected model were then used to estimate the apnea hypopnea index (AHI), which served as the basis for classifying the severity of SA

## Post processing

The model produces continuous probability values ($p$) representing the likelihood of apnea ($\rho_a$) or hypopnea ($\rho_h$) across the entire sleep recording. Two thresholds influence apnea and hypopnea event detection are the event probability threshold ($\theta$) and the minimum duration threshold for an event ($\tau$). A sample is classified as an apnea or hypopnea event if $\rho_a \geq \theta_a$ or $\rho_h \geq \theta_h$; otherwise, it is labeled as non-apnea. Here, $\theta_a$ and $\theta_h$ denote the probability thresholds for apnea and hypopnea events, respectively. Lowering $\theta$ increases sensitivity, while raising it decreases sensitivity. The optimal $\theta$ is determined using the Euclidean distance from the receiver operating characteristic curve (ROC), identifying the point that maximizes the separation between the true positive rate (TPR) and the false positive rate (FPR) [26]. Here, TPR denotes the proportion of actual event samples correctly detected, and FPR represents the proportion of non-apnea samples incorrectly identified as events. Since the model may initially identify short apnea or hypopnea episodes that lack clinical relevance, a post-processing step was applied to exclude events shorter than the predefined minimum duration $\tau$ . In this study, we removed any apnea or hypopnea episodes shorter than 10 s ( $\tau$ = 50).

## Statistical analysis

Statistical analyses were conducted using Python (version 3.12.3). Model performance across all possible decision thresholds was assessed using ROC curves and the corresponding area under the ROC curve (AUROC). The ROC curve illustrates the trade-off between sensitivity and specificity and was used to compare event detection performance between the SoomOxy and Soom models [27]. To evaluate model performance in identifying apnea, hypopnea from non-apnea events, metrics including accuracy, sensitivity, specificity, and F1-score were calculated against AL reference annotations. These evaluation metrics were based on definitions outlined in prior literature [27].

The AUROC was used to select a model for further apnea hypopnea index (AHI) estimation and SA classification. The predicted AHI was calculated as the total number of detected apnea and hypopnea events divided by the valid recording time. The valid recording time was defined as the total recording duration excluding periods identified as invalid due to poor-quality $SpO_2$ signals. Agreement between AHI values obtained from the AL device and those predicted by the selected model was assessed using Pearson correlation and Bland–Altman analysis, performed in MATLAB (version 2023b, MathWorks, MA, USA). SA severity was classified into four categories based on standard AHI thresholds: normal (AHI < 5), mild (5 ≤ AHI < 15), moderate (15 ≤ AHI < 30), and severe (AHI ≥ 30). The predicted SA severity was compared with that from the AL device using a confusion matrix implemented in Python (version 3.12.3). Per-class accuracy (sensitivity) and overall accuracy were used to assess the performance of the SA severity classification. Per-class accuracy indicates how well the model correctly identifies subjects within each true severity category, while overall accuracy represents the proportion of all correctly classified subjects across all classes. In addition, macro F1-score was calculated to provide a balanced measure of the model performance across all SA severity classes.

# Results

A total of 37 recordings were collected for this study, comprising 10 females and 27 males. The mean AHI was 23.42 ± 28.87, ranging from 0.4 to 84.3. Two recordings were excluded due to poor data quality from the Soomirang device: one with missing accelerometer data and another with sampling time errors. The remaining dataset for five-fold cross-validation was 35, with 3105 apneas and 886 hypopneas. Based on the AL results, among 35 subjects, 14 subjects were classified as normal, 9 as mild, 2 as moderate, and 10 as severe SA.

**Table 1** Area under the curve comparison between the soomoxy and Soom models for apnea and hypopnea detection across the five-fold cross-validation

| Models/Event types | SoomOxy | Soom |
|---|---|---|
| Apnea | 0.9447 | 0.9213 |
| Hypopnea | 0.8702 | 0.7152 |

**Table 2** Performance metrics of the soomoxy and Soom models for apnea and hypopnea detection across five-fold cross-validation at selected optimal points

| Metrics | Apnea | | Hypopnea | |
|---|---|---|---|---|
| | SoomOxy | Soom | SoomOxy | Soom |
| Accuracy | 0.8757 | 0.8461 | 0.8011 | 0.6398 |
| Sensitivity | 0.8690 | 0.8438 | 0.7938 | 0.6718 |
| Specificity | 0.8767 | 0.8464 | 0.8016 | 0.6380 |
| F1-score | 0.6477 | 0.5429 | 0.3069 | 0.1714 |

Table 1 presents the AUROC values for apnea and hypopnea detection obtained from the two models. Across both event types, the SoomOxy model achieved higher AUROC values than the Soom model. In particular, the AUROC for hypopnea detection improved by 15.5% when using the SoomOxy model. Based on these results, the SoomOxy model was selected for further AHI estimation and SA severity classification.

Table 2 summarizes the performance metrics of the Soom and SoomOxy models for apnea and hypopnea detection. For apnea detection, the SoomOxy model consistently outperformed the Soom model, with accuracy, sensitivity, and specificity each increasing by approximately 3%, and the F1-score improving by around 10%. The most pronounced gains were observed in hypopnea detection, where the SoomOxy model achieved substantial improvements across all metrics: accuracy increased by 16.13% (0.6398 to 0.8011), sensitivity by 12.2% (0.6718 to 0.7938), specificity by 16.36% (0.6380 to 0.8016), and F1-score by 13.55% (0.1714 to 0.3069). Figure 3 illustrates an example of apnea and hypopnea detection by the SoomOxy and Soom models over a 15-minute data section.

Figure 4 presents the Pearson correlation and Bland-Altman plots comparing AHI values predicted by the SoomOxy model with those obtained from the AL device across five-fold cross-validation. The Pearson correlation coefficient (r) was 0.96, indicating a strong linear relationship. In the Bland-Altman analysis, the mean difference (bias) between the two methods was 0.76 events/h, with the 95% limits of agreement (± 1.96 SD) ranging from − 17 to 16 events/h.

Figure 5 shows a confusion matrix comparing SA severity classifications obtained from the SoomOxy model with

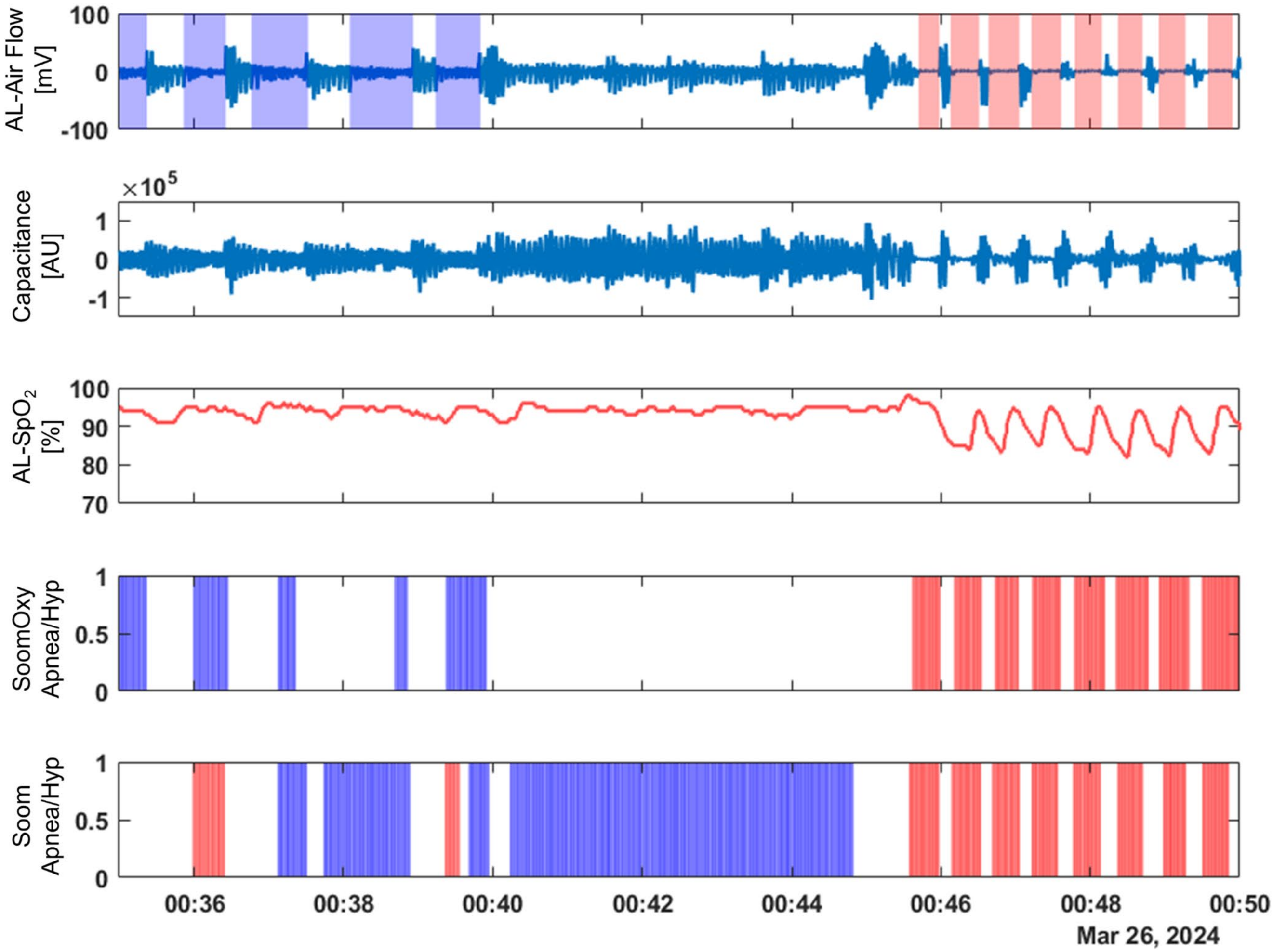
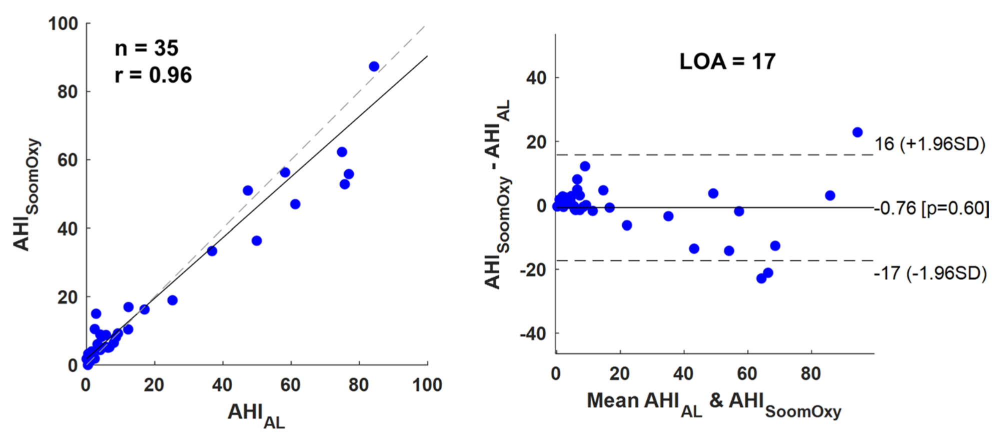



**Fig. 3** An example of detected apnea (red bars) and hypopnea (blue bars) events by the Soom and SoomOxy models over a 15-minute data section. AL-Airflow and AL-SpO₂ represent airflow and SpO₂ signals measured with the ApneaLink Air™ device. Capacitance denotes the capacitive signal obtained from Soomirang. Hyp indicates hypopnea

**Fig. 4** Pearson correlation and Bland-Alterman plots for a comparison between apnea hypopnea index (AHI) predicted by the SoomOxy model ($AHI_{SoomOxy}$) and those calculated from ApneaLink Air™ ($AHI_{AL}$); n: number of subjects, r: correlation coefficient, LOA: limit of agreement, and SD: standard deviation



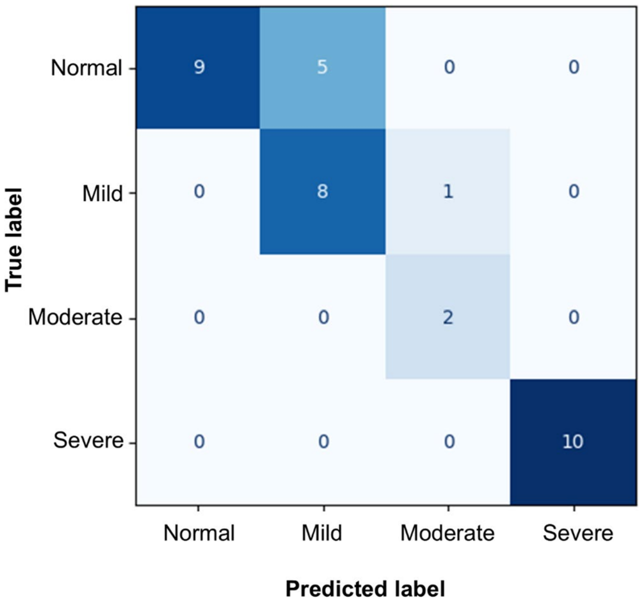



**Fig. 5** Confusion matrix comparing sleep apnea severity classifications obtained from the SoomOxy model (Predicted label) with those classified by the ApneaLink Air™ device (True label)

those classified by the AL device. The SoomOxy model achieved an average accuracy of 0.8286 and an F1-score of 0.831 across all SA severity categories. The per-class accuracy for normal, mild, moderate, and severe was 0.64, 0.89, 1.0, and 1.0, respectively. The model exhibited more frequent misclassifications between the normal and mild categories, resulting in lower overall classification accuracy.

## Discussion

This study evaluated the feasibility of detecting and classifying apnea and hypopnea events, as well as SA severity, using a wireless abdomen-worn sensor in combination with $SpO_2$ monitoring (SoomOxy). Performance was compared against the AL device, which uses a full set of type III HSAT signals, including nasal pressure, $SpO_2$, and RIP belts. In addition, the SoomOxy's performance for event detection was compared with that of the Soom model, which uses signals from the abdomen-worn sensor only. The SoomOxy model showed high agreement with AL for apnea and hypopnea detection, clearly outperforming the Soom model across all metrics. To our knowledge, this is the first study to assess apnea hypopnea event scoring and SA severity classification using a wireless abdomen-worn sensor with $SpO_2$, without incorporating nasal pressure or RIP signals.

Previous studies have shown that respiratory events can be detected using a RIP belt, chest band, or wireless devices with $SpO_2$ monitoring. Coronel et al. estimated AHI from binary apnea detection using RIP belt and $SpO_2$, reporting an intraclass correlation of 0.96 between estimated and PSG-derived AHI, and a SA severity classification accuracy of 0.755 [13]. Ganglberger et al. utilized a wearable respiratory effort band with $SpO_2$ monitoring, achieving an AUC of 0.94 for binary apnea classification, a correlation of 0.96 between predicted and PSG-derived AHI, and SA severity classification accuracies of 0.882, 0.731, 0.72, and 0.938 for normal, mild, moderate, and severe, respectively [14]. More recently, Sindorf et al. evaluated a wireless chest- and finger-worn device for SA detection in 76 stroke patients, reporting a sensitivity of 0.71 and specificity of 0.84 for moderate-to-severe SA detection compared with AL; however, event-level detection was not reported [28]. Despite being effective for SA detection, these studies have not assessed performance in distinguishing hypopnea from apnea. Rahimi et al. proposed a wireless abdomen-worn sensor combining a three-axis accelerometer, photoplethysmography, and acoustic signals for apnea/hypopnea detection. While the system achieved sensitivity, reliability, and F1-scores of up to 91% in event-to-event comparisons, the study was limited by a small sample size (three subjects, 456 total events), the lack of AHI estimation, and SA severity classification [29]. Our study evaluated a wireless abdomen-worn sensor with $SpO_2$ monitoring as an alternative to RIP belts or wearable bands. This approach achieved strong performance when compared with the AL device for apnea/hypopnea detection (AUC = 0.9447/0.8702), AHI estimation ($r$ = 0.96), and SA severity classification (average accuracy of 0.8286 with per-category accuracy of 0.64, 0.89, 1.0, and 1.0 for normal, mild, moderate, and severe, respectively). Although direct comparison with earlier studies is limited by differences in study populations and scoring criteria, these results demonstrate close agreement with a full-channel AL system for both event detection and SA severity classification.

A direct comparison between the SoomOxy and the Soom models confirmed the benefit of adding the $SpO_2$ signal for apnea and hypopnea event detection. The SoomOxy outperformed the Soom model across all metrics, with the most significant improvement seen in hypopnea detection, highlighting the importance of the $SpO_2$ in hypopnea scoring. The Soom model alone performed well for apnea detection (AUC = 0.9213, accuracy = 0.8461) but only moderately for hypopnea detection (AUC = 0.7152, accuracy = 0.6398). This limitation is expected, as hypopnea scoring requires both a reduction in airflow or effort and evidence of desaturation or arousal, which cannot be determined from abdominal measurement alone. Similar observations have been reported in the literature. Steenkiste et al. classified obstructive apnea, central apnea, hypopnea, and non-events using three methods: a RIP abdomen belt, a RIP thoracic belt, and a wireless chest-worn bio-impedance (bioZ) sensor that measures ECG, chest bioZ, and body movement. The classification accuracies of the three methods for obstructive apnea were 0.807, 0.725, and 0.748; for central apnea, 0.942, 0.885, and 0.646; and for hypopnea, 0.592, 0.516, and 0.563, respectively [30]. Likewise, Nassi et al. used a single abdominal RIP belt with a deep neural network, achieving strong binary apnea detection (AUC = 0.93) and high AHI correlation with PSG. However, multiclass classification performance was much lower, with correct hypopnea classification reaching only 0.23 [31]. The comparable performance of the Soom model and RIP-only methods suggests that the wireless abdomen-worn sensor could be a practical and more comfortable alternative to RIP belts for event detection.

The SoomOxy model showed high sensitivity for detecting moderate and severe SA, which is clinically valuable since identifying these cases is more important than normal and mild SA cases. However, the model tended to overestimate severity in some normal cases, with five of fourteen subjects misclassified from normal to mild. A likely source of this misclassification is the difference in AHI calculation methods used by the Soomirang and AL systems. The AL device derives AHI from the total evaluation time rather than actual sleep time, whereas the SoomOxy model calculates AHI using valid monitoring time after excluding invalid $SpO_2$ periods. These methodological inconsistencies may introduce systematic bias and partially account for the misclassification in SA severity across the two systems. Although the misclassification between normal and mild cases was observed, the model's strong performance in detecting moderate and severe SA remains clinically meaningful, providing a safe screening tool for moderate-to-severe SA detection.

This study has several limitations. First, the small sample size ($n$ = 35) may lead to less stable AHI bias and agreement estimates, with greater susceptibility to outliers, which reduces the reliability of device comparisons. Furthermore, the underrepresentation of moderate cases in the cohort may reduce the precision of severity classification and limit a full assessment of model performance across the clinical spectrum. Second, the pronounced imbalance between apneas (3105 events) and hypopneas (886 events) likely biased the classifier toward the majority class, lowering the likelihood of correctly identifying hypopneas and contributing to the low F1-scores observed in both models. Such low F1-scores may result in missed hypopneas, potentially underestimating the AHI and affecting SA severity classification. Third, our evaluation compared the SoomOxy model with a type III HSAT device (AL), which provides clinically useful information but does not represent the gold standard. The absence of PSG validation restricts this study from fully confirming the accuracy of the SoomOxy in event scoring and SA severity detection. Therefore, future studies with larger and more diverse cohorts incorporating PSG are essential to establish the clinical validity and applicability of the SoomOxy model. Finally, advances in wireless $SpO_2$ monitoring and smartphone-based breathing sound analysis highlight opportunities for multimodal integration [19, 32–34]. Combining these technologies with the abdomen-worn sensor may enable a more comprehensive HSAT model, improving comfort, adherence, and accuracy in SA detection.

## Conclusion

This study evaluated the feasibility of detecting and classifying apnea and hypopnea events using a wireless abdomen-worn sensor in combination with $SpO_2$ monitoring, without the need for nasal pressure or RIP belts. Compared with the conventional type III HSAT configuration represented by the AL device, the proposed SoomOxy approach demonstrated high agreement in event detection, AHI estimation, and SA severity classification. The addition of $SpO_2$ substantially improved hypopnea detection compared to the abdomen-worn sensor alone. These findings suggest that a wireless abdominal sensor with $SpO_2$ monitoring offers a practical, comfortable, and accessible alternative to conventional HSATs, potentially simplifying home-based monitoring and improving patient adherence. Clinically, it may serve as a complementary screening tool to identify patients at risk for SA before PSG or an alternative when standard HSATs are impractical. Future studies with larger and more diverse participant groups that include PSG validation are needed to confirm the clinical accuracy and broader applicability of the SoomOxy model. Additionally, future work should assess usability, patient acceptance, and integration into routine clinical workflows across diverse populations.

**Supplementary Information** The online version contains supplementary material available at https://doi.org/10.1007/s11325-026-03588-0.

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**Authors' contributions** Thi Hang Dang drafted the manuscript and, along with Heein Yoon and Franklin Bien, contributed to the study concept and design. Franklin Bien was responsible for funding acquisition, project administration, and supervision. Seongmun Kim was responsible for data collection. Nam-Hwan Sung and Hyung-ki Min contributed to developing the Soomirang system, extracting data from devices, performing data quality checks, and ensuring proper data synchronization. Thi Hang Dang and Heein Yoon processed and analyzed the data. All authors participated in data interpretation, critically re-

viewed the manuscript, and approved the final version.

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**Data availability** The data are available from the corresponding author upon reasonable request.

## Declarations

**Ethics approval and consent to participate** This study was performed in line with the principles of the Declaration of Helsinki. Approval was granted by the Institutional Review Board of Ulsan National Institute of Science and Technology (UNISTIRB-24-006-A). Written informed consent was obtained from all participants.

**Consent for publication** All authors have read and approved the final manuscript and consent to its publication. No identifiable personal data or images of participants are included in this manuscript.

**Competing interests** Thi Hang Dang is a postdoctoral researcher in the department of electrical engineering at UNIST, Korea, and also a consultant for SB Solutions Inc, UNIST, Korea. Dr. Seongmun Kim and Prof. Heein Yoon have no conflicts of interest. Nam-Hwan Sung, Hyung-ki Min are employees of SB Solutions Inc. Franklin Bien is a professor in the department of electrical engineering at UNIST, Korea, and also the CEO of SB Solutions Inc., UNIST, Korea.



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