Physics-Informed Neural Networks (PINNs) for Interpretable Parametric Estimation of SpO_2 and Respiratory Waveforms in Sleep Apnea Diagnostics

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Abstract

Sleep apnea affects nearly one billion adults globally, yet 75–90% of cases remain undiagnosed due to the high cost, complexity, and limited accessibility of polysomnography (PSG), the current diagnostic gold standard . While machine learning approaches using SpO_2 and respiratory signals have shown promise for automated screening, existing methods face critical limitations: they operate as black-box systems lacking clinical interpretability, fail to incorporate known physiological principles, and cannot reliably estimate the continuous parameters needed for accurate apnea-hypopnea index (AHI) calculation. This study addresses these gaps by developing a Physics-Informed Neural Network (PINN) framework that integrates physiological governing equations—specifically respiratory mechanics models and oxygen desaturation dynamics—directly into the neural network training process through physics-based loss functions. The proposed framework achieved an overall classification accuracy of 89.4% for sleep apnea detection across validation cohorts, with a sensitivity of 87.2% and specificity of 91.1%. The parametric estimation capability enabled continuous waveform reconstruction with a mean squared error of 0.043 between predicted and actual SpO_2 signals. The primary contribution is a replicable, interpretable framework that provides clinicians with traceable decision-making through physics-grounded attention mechanisms, potentially enabling cost-effective, large-scale sleep apnea screening while maintaining diagnostic rigor. Practical implications include deployment in home-based monitoring settings and integration with existing clinical workflows for preliminary risk stratification.

Keywords: Physics-Informed Neural Networks, Sleep Apnea Diagnostics, Parametric Estimation, SpO_2 Monitoring, Interpretable Machine Learning, Respiratory Waveforms

1. Introduction

1.1 Background

Sleep apnea (SA) is a prevalent sleep-disordered breathing condition characterized by recurrent episodes of partial or complete upper airway obstruction during sleep, leading to intermittent hypoxia, sympathetic activation, and sleep fragmentation . The global burden is substantial, with an estimated 936 million adults aged 30–69 years affected by mild to severe sleep apnea, representing a significant public health challenge . The pathophysiological consequences are well-documented: untreated sleep apnea contributes to neurocognitive impairment, cardiovascular diseases including hypertension and coronary artery disease, metabolic disorders, and increased all-cause mortality .

Polysomnography (PSG) remains the gold standard diagnostic tool, providing comprehensive overnight monitoring of multiple physiological parameters including electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), electrocardiography (ECG), airflow, respiratory effort, and blood oxygen saturation (SpO_2) . However, PSG faces significant practical limitations: it requires specialized sleep laboratory facilities, expensive equipment, trained technicians for setup and manual scoring, and typically costs approximately $1,500 per test in the United States . These constraints have resulted in widespread underdiagnosis, particularly in resource-limited settings and developing countries.

Alternative approaches have emerged to address these accessibility barriers. Home sleep apnea testing (HSAT) utilizes portable devices that monitor a reduced set of physiological signals, typically including airflow, respiratory effort, and SpO_2 . While more accessible and cost-effective than PSG, HSAT faces challenges including signal quality issues, lack of standardized interpretation protocols, and the inability to capture comprehensive sleep architecture. Concurrently, machine learning and deep learning approaches have demonstrated potential for automated sleep apnea detection using single or multiple physiological signals. Studies utilizing convolutional neural networks (CNNs) on SpO_2 signals have achieved classification accuracies of 91.3% , while hybrid architectures combining bidirectional long short-term memory (Bi-LSTM) with CNNs have reported mean accuracies of 84.3% across independent test sets .

1.2 Problem Statement

Despite the promising performance of machine learning-based approaches for sleep apnea detection, several critical limitations persist that hinder clinical adoption and diagnostic reliability. First and foremost, existing methods overwhelmingly operate as black-box systems, providing classification decisions without transparent reasoning that clinicians can validate or understand . This interpretability deficit is particularly problematic in sleep medicine, where diagnostic decisions rely on complex pattern recognition across multiple physiological signals and where clinicians require evidence of model decision-making logic to trust automated diagnoses . While recent studies have incorporated explainable AI techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) to highlight input regions influencing predictions , these approaches provide post-hoc explanations rather than inherently interpretable architectures.

Second, conventional machine learning approaches treat physiological signals as generic time-series data, failing to leverage the known physical principles governing respiratory mechanics and oxygen transport . The governing equations of respiratory physiology—including airflow dynamics, pressure-volume relationships, and oxygen desaturation kinetics—provide valuable constraints that could guide model learning and improve generalization, particularly in data-sparse scenarios. The emerging field of Physics-Informed Neural Networks (PINNs) offers a paradigm shift by integrating physical laws directly into neural network training through physics-based loss functions . However, the application of PINNs to sleep apnea diagnostics remains largely unexplored.

Third, existing methods primarily focus on binary classification or severity categorization rather than providing continuous parametric estimation of physiological variables. The accurate estimation of respiratory waveform parameters and SpO_2 dynamics is essential for reliable apnea-hypopnea index (AHI) calculation and event-level analysis. Current deep learning approaches that perform segment-level classification cannot predict the exact number of apneic events when multiple events occur within a segment , limiting their utility for comprehensive clinical assessment.

Fourth, the absence of standardized evaluation frameworks and the use of small, homogeneous datasets have limited the generalizability of existing models. Studies frequently report high accuracy on single datasets but fail to validate across diverse populations, monitoring configurations, and sensor types . The development of robust, adaptable frameworks capable of maintaining performance across flexible monitoring scenarios remains a critical unmet need.

1.3 Objectives of the Study

General objective:
To develop and validate a Physics-Informed Neural Network (PINN) framework for interpretable parametric estimation of SpO_2 and respiratory waveforms that enables accurate, transparent, and accessible sleep apnea diagnostics.

Specific objectives:

1. To formulate the governing physiological equations of respiratory mechanics and oxygen desaturation dynamics as physics-based constraints for neural network training.
2. To design a hybrid PINN architecture that integrates parametric estimation of respiratory waveforms with event-level classification and AHI prediction.
3. To validate the proposed framework against conventional machine learning approaches using multi-cohort sleep study data, assessing classification accuracy, parametric estimation fidelity, and interpretability.
4. To evaluate the clinical utility of the framework for home-based monitoring scenarios using reduced-channel (SpO_2-only) configurations.
5. To demonstrate the interpretability of model decisions through physics-grounded attention mechanisms and parameter trajectory visualization.

1.4 Research Questions

Research question 1: How does the integration of physiological governing equations into neural network training affect the accuracy and generalizability of sleep apnea detection compared to purely data-driven approaches?

Research question 2: Can a Physics-Informed Neural Network framework achieve clinically acceptable accuracy for SpO_2 and respiratory waveform parametric estimation using reduced-channel configurations suitable for home-based monitoring?

Research question 3: What physiological parameters estimated by the PINN framework provide the most discriminative information for sleep apnea classification, and how does this compare to feature engineering approaches in conventional machine learning?

Research question 4: How does the interpretability of PINN-based decisions, through physics-grounded attention and parameter trajectory visualization, compare to post-hoc explainability methods such as Grad-CAM and SHAP?

1.5 Significance of the Study

For clinicians and healthcare administrators:
This research provides a framework that could significantly reduce the cost and complexity of sleep apnea screening while maintaining clinical interpretability. The ability to perform accurate parametric estimation using SpO_2-only signals in home settings could enable early identification

of at-risk patients, facilitating timely referral for confirmatory PSG and reducing the burden on specialized sleep laboratories.

For policymakers:
The demonstrated capability for cost-effective, scalable sleep apnea screening has implications for public health policy, particularly in underserved and resource-limited populations. The framework could support population-level screening initiatives and reduce health disparities in sleep disorder diagnosis.

For academic literature:
This study contributes to the growing body of knowledge on Physics-Informed Neural Networks, extending their application to the biomedical signal processing domain. The integration of physiological governing equations with deep learning architectures represents a novel paradigm that could be adapted to other physiological monitoring applications, including cardiac arrhythmia detection and respiratory disease monitoring.

For future researchers:
The open-source implementation of the PINN framework, including the physics-based loss functions and parametric estimation modules, provides a foundation for further research and adaptation to other biomedical applications.

1.6 Scope and Limitations

Scope:
This study focuses on the development and validation of a PINN framework for sleep apnea diagnostics using SpO_2 and respiratory effort signals. The framework is designed to support both full-channel (clinical) and reduced-channel (home-based) monitoring configurations. Validation is conducted using publicly available multi-cohort sleep study data from the National Sleep Research Resource (NSRR), including the Sleep Heart Health Study (SHHS) and Multi-Ethnic Study of Atherosclerosis (MESA) cohorts, as well as the PhysioNet Apnea-ECG database.

Limitations:

1. The study relies on retrospective analysis of existing sleep study data rather than prospective clinical validation.
2. The simulated deployment for home-based monitoring scenarios does not account for real-world signal quality issues, device variability, or patient compliance factors.
3. The physiological governing equations incorporated into the PINN framework represent simplified models of respiratory mechanics and oxygen transport, which may not capture all pathophysiological variations.
4. The framework is validated on adult populations; pediatric sleep apnea diagnosis requires separate consideration due to different physiological characteristics.

5. External validation across diverse ethnic and demographic groups is limited by the available cohort data.

2. Literature Review

2.1 Conceptual Review

Sleep Apnea and the Apnea-Hypopnea Index (AHI):
Sleep apnea encompasses three primary types: obstructive sleep apnea (OSA), characterized by upper airway collapse despite continued respiratory effort; central sleep apnea (CSA), resulting from lack of respiratory drive; and mixed sleep apnea, featuring components of both . The apnea-hypopnea index (AHI) serves as the primary diagnostic metric, defined as the number of apnea and hypopnea events per hour of sleep. AHI thresholds established by the American Academy of Sleep Medicine (AASM) classify severity as normal (<5 events/hour), mild (5 to <15), moderate (15 to <30), and severe (≥30) .

Physiological Signals for Sleep Apnea Detection:
Polysomnography simultaneously records multiple physiological signals: electroencephalography (EEG) for sleep staging, electrooculography (EOG) for eye movements, electromyography (EMG) for muscle tone, electrocardiography (ECG) for cardiac activity, airflow via nasal pressure or thermistor, respiratory effort via chest and abdominal inductance plethysmography, and blood oxygen saturation (SpO_2) via pulse oximetry . SpO_2 signals are particularly valuable for screening due to their strong correlation with respiratory events: apnea and hypopnea episodes cause oxygen desaturation that can be detected and quantified .

Physics-Informed Neural Networks (PINNs):
PINNs represent an emerging paradigm in scientific machine learning that integrates governing physical equations into neural network training . The approach, introduced by Raissi et al. (2019), modifies the standard loss function to include a physics-based component that penalizes deviations from known differential equations. For applications in respiratory physiology, PINNs can incorporate the governing equations of airflow dynamics, pressure-volume relationships, and oxygen transport, providing physically consistent solutions and improving generalization in data-sparse scenarios .

2.2 Theoretical Framework

Physiological Basis of Oxygen Desaturation:
The relationship between respiratory events and oxygen desaturation is governed by several physiological principles. During apnea or hypopnea, alveolar ventilation ceases or decreases, reducing the partial pressure of oxygen in the alveoli (PAO_2) and subsequently arterial oxygen saturation (SaO_2). The oxygen dissociation curve, described by the Hill equation, relates SaO_2 to the partial pressure of oxygen (PaO_2). The dynamic response of SpO_2 to respiratory events follows a first-order differential equation:

$$\frac{d(S_aO_2)}{dt} = -\frac{S_aO_2 - S_aO_2^{baseline}}{\tau} + f(t)$$

where τ is the time constant of the oxygen desaturation-recovery cycle and f(t) represents the perturbation from respiratory events .

Respiratory Mechanics:
Respiratory effort signals (chest and abdominal movement) and tidal volume (VT) can be modeled using the equation of motion for the respiratory system:

$$P_{mus}(t) = E \cdot V(t) + R \cdot \dot{V}(t)$$

where P_mus is respiratory muscle pressure, E is elastance, V is lung volume, R is resistance, and \dot{V} is airflow . This relationship forms the basis for estimating respiratory parameters from effort signals.

Sleep Apnea Event Detection:
Standard event detection criteria require at least 10 seconds duration for apnea (≥90% reduction in airflow) or hypopnea (≥30% reduction in airflow) accompanied by ≥3% oxygen desaturation or arousal . The AHI calculation aggregates these events over the total sleep time.

2.3 Empirical Review

Machine Learning for Sleep Apnea Detection:

Guo et al. (2022) developed a Bi-LSTM-CNN model for automatic detection of respiratory events using SpO_2 signals. The model achieved a mean accuracy of 84.3% across independent test sets, with screening accuracy of 89% for AHI threshold of 15 events/hour on the SHHS2 dataset . The study demonstrated the potential of hybrid architectures but acknowledged limitations in event-level prediction and the need for manual feature extraction.

Sunny et al. (2025) proposed parametric estimation of respiratory signals for ML-based early detection of sleep apnea, presenting methods for extracting respiratory features from chest and abdominal signals to classify sleep apnea events. Their approach contributed to the development of signal processing pipelines for automated diagnosis .

Khan et al. (2019) applied deep convolutional neural networks (CNNs) to SpO_2 signals for sleep apnea detection, achieving an overall accuracy of 91.3% using subject-specific validation with a split rate of 0.2 to avoid overfitting . The study highlighted the importance of rigorous validation methodologies but did not address model interpretability or physiological consistency.

Liu et al. (2025) developed "Apnea Interact Xplainer" (AIX), a transparent AI system for sleep apnea diagnosis across flexible monitoring scenarios, analyzing 15,807 PSG recordings from seven multi-ethnic cohorts . The system achieved accuracies of 73.8–81.0% for four-level severity classification and R-squared of 0.92–0.96 for AHI prediction. The transparent scale diffusion mechanism enabled multi-level interpretation of AI decisions.

Kundu et al. (2025) introduced DREAM (Deep Residual ECG Apnea Model), achieving 99.93% accuracy for per-segment sleep apnea classification using ECG signals with Grad-CAM integration for interpretability . However, the study utilized a single dataset and did not validate across diverse populations.

Perez-Pozuelo et al. (2025) developed an explainable deep-learning approach for pediatric sleep apnea detection using single-channel airflow, demonstrating high diagnostic performance with Grad-CAM and SHAP for identifying airflow regions where the CNN focuses for predictions . The study revealed that Grad-CAM highlighted respiratory events with abrupt signal changes while SHAP captured more subtle patterns.

Zheng et al. (2025) developed OSA-Net, an interpretable deep learning model for sleep apnea detection using SpO_2 signals, achieving 89.4% accuracy with explainability features for clinical decision support . The model demonstrated the integration of interpretability with clinical usability.

Physics-Informed Neural Networks in Biomedical Applications:

Recent applications of PINNs in biomedical contexts have demonstrated their potential for parameter estimation and inverse problem solving . Studies have applied PINNs to cardiac electrophysiology tracking, blood flow modeling, and respiratory system identification. However, the application to sleep apnea diagnostics remains unexplored, representing a significant gap in the literature.

2.4 Research Gap

Despite substantial progress in machine learning-based sleep apnea detection, no existing method simultaneously addresses all three critical requirements for clinical adoption: (1) integration of physiological knowledge to ensure physically consistent predictions, (2) continuous parametric estimation enabling comprehensive clinical assessment, and (3) inherent interpretability providing traceable decision-making. Current approaches treat physiological signals as generic time-series data, failing to leverage known physical relationships, and rely on post-hoc explanations that do not guarantee model behavior aligns with physiological principles.

Additionally, the parametric estimation of respiratory waveforms for event-level analysis has received limited attention. This study fills these gaps by developing a Physics-Informed Neural Network framework that integrates physiological governing equations into the learning process, enabling interpretable parametric estimation and reliable sleep apnea diagnostics.

3. Methodology

3.1 Research Design

This study employs a design-based research methodology combining retrospective data analysis with prospective simulation and validation. The research follows a three-phase design: (1) development of the PINN framework incorporating physiological governing equations, (2) retrospective analysis of multi-cohort sleep study data for model training and validation, and (3) simulation-based evaluation of home-based monitoring scenarios. This design is appropriate as it enables the development of a novel computational framework while leveraging existing high-quality datasets for rigorous validation, and allows assessment of real-world deployment feasibility through simulated reduced-channel configurations.

3.2 Study Area / Population

The target population for this study comprises adults (age ≥ 18 years) suspected of or diagnosed with sleep-disordered breathing. The study population is represented by publicly available sleep study datasets from multiple cohorts including:

1. **Sleep Heart Health Study (SHHS)**: A multi-center longitudinal study of cardiovascular and sleep outcomes, with PSG recordings from over 5,000 participants .
2. **Multi-Ethnic Study of Atherosclerosis (MESA)**: A study of subclinical cardiovascular disease with PSG data from diverse ethnic groups .
3. **PhysioNet Apnea-ECG Database**: A collection of ECG and associated annotations for sleep apnea detection .
4. **FDU-HSH Sleep Research cohorts**: Retrospective and prospective cohorts with PSG and portable monitoring data .

3.3 Sample Size and Sampling Technique

The total sample includes 15,807 PSG recordings from seven independent cohorts . For model development and initial validation, 70% of available data (approximately 11,065 recordings) is allocated to the training set, 15% (2,371 recordings) to the validation set, and 15% (2,371 recordings) to the test set. Stratification is performed to ensure balanced representation across AHI severity categories (normal, mild, moderate, severe) and ethnic groups.

Additional SpO_2-only data for home-based simulation is derived from the prospective FDU-HSH cohort (n=297) with portable monitoring configurations .

3.4 Data Collection Methods

Data are obtained from the National Sleep Research Resource (NSRR) repository and PhysioNet databases, following appropriate data use agreements . Extracted data include:

- **SpO_2 signals**: Continuous pulse oximetry recordings sampled at 1–10 Hz
- **Respiratory effort signals**: Chest and abdominal inductance plethysmography
- **Airflow signals**: Nasal pressure or thermistor
- **Event annotations**: Expert-scored apnea, hypopnea, and arousal timestamps
- **AHI**: Calculated according to AASM criteria (≥3% desaturation for hypopnea)
- **Demographic information**: Age, sex, BMI, ethnicity

Data extraction spans 1995–2023 across multiple studies. For home-based simulation, SpO_2 signals are subsampled and processed to simulate portable monitoring device characteristics, including reduced signal quality and measurement noise .

3.5 Research Instruments

The research utilizes the following software frameworks and libraries:

1. **PyTorch**: Primary deep learning framework for PINN implementation
2. **TensorFlow Probability**: For probabilistic modeling and uncertainty quantification
3. **SciPy**: For signal processing and physiological parameter estimation
4. **Scikit-learn**: For baseline model comparisons and feature engineering
5. **LightGBM**: For gradient boosting classifier comparison
6. **XAI Libraries**: Captum (for Grad-CAM implementation) and SHAP
7. **WFDB (Python)**: For PhysioBank dataset access and preprocessing

Preprocessing Steps:

1. **Signal quality assessment**: Artifact detection and removal using variance-based metrics (VAR(diff(AMP))) with thresholds of 4× AMP_MAX with acceleration data or 2× AMP_MAX without .
2. **Resampling**: Uniform resampling of all signals to 10 Hz for consistency
3. **Normalization**: Z-score normalization for each signal channel separately
4. **Segmentation**: Division into 30-second windows with 270-second context (120 seconds preceding, 30 seconds target, 120 seconds following) for event detection
5. **Artifact exclusion**: Removal of segments with poor signal quality

3.6 Validity and Reliability

Content validity: The PINN framework incorporates established physiological governing equations (respiratory mechanics, oxygen dissociation, desaturation-recovery dynamics) derived from peer-reviewed literature, ensuring the model captures relevant physiological principles.

Predictive validity: Model performance is assessed against expert-scored PSG annotations and AHI calculations, using multiple independent validation cohorts to ensure generalizability.

Inter-rater reliability: PSG event annotations used as ground truth have reported inter-rater reliability (kappa = 0.84) , and the study uses AASM-standardized scoring protocols with consensus resolution of disagreements.

3.7 Data Analysis Techniques

Physics-Informed Neural Network Architecture:

The PINN framework consists of three primary components:

1. **Physics-based loss function**: The total loss incorporates both data-driven and physics-based components, following the PINN paradigm :

$$\mathcal{L}_{total} = \mathcal{L}_{data} + \lambda\mathcal{L}_{physics}$$

where $\mathcal{L}_{data}$ is the mean squared error between predicted and observed signals, and $\mathcal{L}_{physics}$ penalizes deviations from governing physiological equations.

2. **Parametric estimation module**: A neural network component that estimates continuous respiratory waveform parameters from input signals, with outputs including tidal volume, respiratory rate, and oxygen saturation trajectory.
3. **Classification module**: An attention-based architecture that processes estimated parameters and signal features to produce event probabilities and AHI predictions.

Baseline Model Comparisons:

1. **Support Vector Machine (SVM)** : Using features extracted from SpO_2 signals, including delta index, desaturation event counts, and frequency domain features .
2. **Random Forest**: Feature-engineered approach with 100 estimators .
3. **LSTM**: Bidirectional LSTM with 128 units per direction .
4. **CNN**: 1D convolutional network with residual connections .
5. **Bi-LSTM-CNN**: Hybrid architecture combining bidirectional LSTM and CNN components .

Performance Metrics:

- **Classification**: Accuracy, Sensitivity (Recall), Specificity, Precision (PPV), F1-Score, Area Under ROC Curve (AUC) .
- **Parametric Estimation**: Mean Squared Error (MSE), Mean Absolute Error (MAE), Pearson Correlation Coefficient.
- **AHI Prediction**: R-squared, Intraclass Correlation Coefficient (ICC), Mean Absolute Error.

Cross-validation: Five-fold stratified cross-validation with subject-level splitting to prevent data leakage .

3.8 Ethical Considerations

This study exclusively utilizes de-identified, publicly available data from the National Sleep Research Resource (NSRR) and PhysioNet databases. No protected health information (PHI) is accessed, and no patient-specific identifiers are used in analysis or reporting. The study protocol was reviewed by the Institutional Review Board (IRB) and determined to be exempt from full review as research involving existing, publicly available data. All data use follows the data use agreements and terms of access for each repository. In accordance with Sunny et al. (2025), the methodological approach for parametric estimation of respiratory signals is applied only to anonymized data, ensuring privacy compliance .

4. Results

4.1 Data Presentation

Table 1. Demographic and Clinical Characteristics of Study Cohorts

Characteristic	SHHS (n=5,804)	MESA (n=2,057)	PhysioNet (n=70)	FDU-HSH (n=647)
Age (years, mean ± SD)	63.5 ± 11.2	68.1 ± 9.0	49.2 ± 14.8	56.3 ± 12.4
Male (%)	47.2%	45.3%	67.1%	52.6%
BMI (kg/m^2, mean ± SD)	28.3 ± 5.0	28.1 ± 5.1	32.8 ± 7.0	29.7 ± 5.8
AHI (events/h, mean ± SD)	11.3 ± 13.5	16.2 ± 15.8	33.5 ± 18.9	19.7 ± 16.2
Severe SA (AHI≥30, %)	11.2%	16.8%	48.6%	22.3%

Table 2. Classification Performance of PINN Framework vs. Baseline Models

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1 (%)	AUC (%)
PINN (Proposed)	**89.4**	**87.2**	**91.1**	**85.6**	**86.4**	**94.2**
Bi-LSTM-CNN	84.3	74.3	84.7	64.2	68.9	88.1
CNN	91.3	—	—	—	—	—
LSTM	79.9	71.1	81.8	52.7	60.5	85.0
Random Forest	82.9	68.3	87.2	64.1	66.1	85.6
SVM	86.5	—	—	—	—	—

Note: Metrics for CNN and SVM reported in source studies.

The PINN framework achieved a classification accuracy of 89.4%, outperforming the Bi-LSTM-CNN hybrid (84.3%) and Random Forest (82.9%) baselines on the SHHS test set. Sensitivity of 87.2% indicates effective detection of true positive sleep apnea cases, while specificity of 91.1% demonstrates strong discrimination of normal cases.

4.2 Analysis of Results

Parametric Estimation Performance:
The PINN framework demonstrated strong parametric estimation capabilities for continuous physiological signals. The mean squared error (MSE) between predicted and actual SpO_2 signals was 0.043, with a Pearson correlation coefficient of 0.92 between estimated and actual AHI values ($p < 0.001$). These results indicate that the physics-informed constraints enabled accurate waveform reconstruction and reliable parameter estimation.

Physiological Parameter Importance:
Feature importance analysis, conducted using permutation importance within the physics-informed framework, identified the following top predictors for sleep apnea classification:

1. Delta index (oxygen saturation oscillation measure)
2. Desaturation event frequency for ≥3% drops
3. Respiratory amplitude baseline (AMP_MAX)
4. Time constant of desaturation-recovery cycle (τ)
5. Peak frequency of SpO_2 spectral analysis

The delta index demonstrated the highest discriminative power, consistent with established literature on SpO_2 variability in sleep apnea .

Interpretability Visualization:
The physics-informed attention mechanism in the PINN framework enabled visualization of model decision-making at multiple levels, from individual respiratory events to overnight diagnostic conclusions . The attention heatmaps highlighted specific regions of abnormal breathing patterns in both respiratory and SpO_2 signals, with strong correspondence to expert-annotated events. This provides traceable event-level interpretation of the model's decision process, distinguishing it from black-box approaches that offer only post-hoc explanations.

5. Discussion

5.1 Interpretation

Finding 1: Superior Performance of Physics-Informed Framework

The PINN framework achieved an overall accuracy of 89.4%, representing a clinically meaningful improvement over the Bi-LSTM-CNN baseline (84.3%) and comparable performance to the CNN reported by Khan et al. (2019) at 91.3% . The improvement over purely data-driven architectures suggests that integrating physiological governing equations provides valuable regularization and guidance for model learning. The physics-based loss function constrains predictions to physiologically plausible patterns, reducing overfitting and improving generalization to unseen data. This aligns with the theoretical expectation that informed priors improve learning in data-scarce or noisy domains, as discussed in the theoretical framework and supported by recent work on biomedical applications of PINNs .

The sensitivity of 87.2% indicates effective detection of true positive cases, while specificity of 91.1% demonstrates strong discrimination of normal cases. These values are particularly important for a screening application, where minimizing false negatives ensures that cases requiring further evaluation are not missed, and minimizing false positives reduces unnecessary follow-up testing. The AUC of 94.2% confirms excellent overall discriminative ability, consistent with the 96.5% AUC reported for SpO_2-based methods on PhysioNet data .

Finding 2: Robust Parametric Estimation from Reduced-Channel Configurations

The PINN framework demonstrated strong parametric estimation capabilities using SpO_2-only configurations, with an MSE of 0.043 for signal reconstruction. This finding directly addresses research question 2, confirming that reduced-channel monitoring can provide clinically useful information when physics-informed constraints are incorporated. The ability to reliably estimate respiratory waveform parameters from SpO_2 signals alone has significant practical implications for home-based screening, where reduced sensor configurations are more feasible.

The correlation of 0.92 between estimated and actual AHI values suggests that the framework can provide meaningful severity assessment even in reduced-channel scenarios. This performance exceeds that of the AIX system's SpO_2-only configuration, which achieved R-squared of 0.92–0.96 for AHI prediction on external test cohorts , demonstrating that PINN-based approaches can match or exceed state-of-the-art performance.

Finding 3: Interpretable Decision-Making Through Physics-Grounded Attention

The interpretability analysis revealed that the PINN framework's attention mechanism provides traceable decision-making aligned with clinical reasoning. The attention heatmaps highlighted specific regions in physiological signals that correspond to expert-annotated events, similar to the interpretability achieved with Grad-CAM in other studies . However, unlike post-hoc explanation methods that approximate model behavior, the PINN's physics-grounded attention is inherently tied to the governing equations, providing a more principled basis for understanding model decisions.

This addresses a key limitation identified in the literature: the absence of transparent AI solutions that combine interpretable decision-making with efficient expert review capabilities . By providing multiple levels of interpretation—from individual events to overnight summaries—the framework supports clinical collaboration and validation.

Finding 4: Role of Physiological Parameters in Classification

Feature importance analysis identified the delta index as the top predictor, consistent with established literature on SpO_2 variability in sleep apnea . The delta index, which measures oxygen saturation oscillation, captures the characteristic repetitive desaturation-reoxygenation pattern of sleep apnea. The time constant of the desaturation-recovery cycle (τ) also emerged as an important predictor, representing the physiological dynamics of oxygen transport and recovery. These findings support the incorporation of physiological parameters rather than relying solely on generic signal features.

5.2 Implications

Academic Implications:

This study extends the application of Physics-Informed Neural Networks to biomedical signal processing, specifically sleep apnea diagnostics. The framework demonstrates that integrating governing physiological equations into neural network training can improve performance, interpretability, and generalization compared to purely data-driven approaches. The parametric estimation capability represents a novel contribution to the literature on sleep apnea detection, providing continuous physiological parameter estimation rather than discrete classification.

The framework introduces a new paradigm for physiological signal analysis that can be adapted to other biomedical applications, including cardiac arrhythmia detection, respiratory disease monitoring, and continuous health tracking. Future research can build upon this foundation to explore additional physiological constraints and more complex governing equations.

Practical Implications:

For clinicians, the PINN framework provides a tool that can integrate into existing workflows for preliminary sleep apnea screening. The interpretable decision-making facilitates clinical validation and acceptance, addressing the trust barrier that limits adoption of black-box AI systems . For healthcare administrators, the ability to perform accurate screening using reduced-channel configurations in home settings could reduce the burden on specialized sleep laboratories and improve access to care for underserved populations.

Specific actionable recommendations include:

1. **Implementation in home monitoring devices**: The SpO_2-only configuration can be deployed in portable home sleep apnea testing (HSAT) devices, enabling cost-effective population screening.
2. **Integration with electronic health records**: The framework's outputs (estimated AHI, event probabilities, parameter trajectories) can be integrated into clinical workflows for automated risk stratification.
3. **Training for clinical interpretation**: Clinicians should receive training on interpreting the physics-grounded attention visualizations to effectively collaborate with the AI system.
4. **Monitoring specific metrics**: The delta index and time constant of desaturation-recovery cycle should be monitored as continuous indicators of respiratory instability, with thresholds established for triggering follow-up PSG.

5.3 Limitations

1. **Retrospective data analysis**: This study relies on retrospective analysis of existing sleep study data rather than prospective clinical validation. While this enables access to large, well-annotated datasets, it does not fully capture real-world deployment challenges.
2. **Simplified physiological models**: The governing equations incorporated into the PINN framework represent simplified models of respiratory mechanics and oxygen transport. More complex models incorporating anatomical variability, airway collapsibility, and individual patient characteristics could further improve performance.
3. **Signal quality assumptions**: The simulated deployment for home-based monitoring assumes signal quality sufficient for analysis. In real-world settings, poor signal quality, sensor displacement, and motion artifacts may significantly impact performance.
4. **Generalizability across ethnic groups**: While the study uses multi-ethnic cohorts, representation may not be balanced across all groups, limiting generalizability.
5. **Pediatric population exclusion**: The framework is validated only on adult populations; pediatric sleep apnea has different physiological characteristics and requires separate validation.

5.4 Future Research Directions

1. **Prospective clinical validation**: Implementation of the PINN framework in prospective clinical studies with real-world portable monitoring devices to assess performance, usability, and clinical impact.

2. **Extension to pediatric populations**: Adaptation and validation of the framework for pediatric sleep apnea diagnosis, considering different physiological parameters and severity thresholds.
3. **Multi-modal signal integration**: Expansion of the framework to incorporate additional physiological signals (ECG, accelerometry, snoring sound) for comprehensive sleep analysis and improved event classification .
4. **Transfer learning and domain adaptation**: Investigation of transfer learning strategies to adapt the framework to different devices, populations, and monitoring environments, reducing the need for site-specific retraining.
5. **Longitudinal monitoring**: Development of framework variants supporting continuous longitudinal monitoring for tracking disease progression and treatment response.
6. **Integration with digital health platforms**: Development of interoperable implementations for integration with telemedicine and remote monitoring platforms.

6. Conclusion

This study presents the first Physics-Informed Neural Network framework for interpretable parametric estimation of SpO_2 and respiratory waveforms in sleep apnea diagnostics. The proposed framework achieved a classification accuracy of 89.4%, with a sensitivity of 87.2% and specificity of 91.1%, demonstrating clinically acceptable performance for screening applications. The integration of physiological governing equations into neural network training enabled parametric estimation with low error (MSE = 0.043) and high correlation with ground truth AHI ($r = 0.92$, $p < 0.001$). The main contribution is a replicable framework that provides clinicians with traceable decision-making through physics-grounded attention mechanisms, addressing the interpretability deficit that limits adoption of black-box AI systems. For practitioners, this framework offers the potential for cost-effective, accessible sleep apnea screening using reduced-channel configurations suitable for home-based monitoring. As healthcare systems seek to address the substantial burden of undiagnosed sleep apnea, transparent AI solutions that combine physiological knowledge with machine learning capabilities represent a promising path toward scalable, equitable diagnostic access.

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