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ORIGINAL

Remote monitoring of respiratory diseases using AI that analyzes cough sounds and breathing patterns

Monitoreo remoto de enfermedades respiratorias con IA que analiza sonidos de tos y patrones respiratorios

Rekha Sharma[1*]

[1]Himachal Pradesh University, India.

***Corresponding author:** Rekha Sharma, rh@hpuniv.ac.in

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ABSTRACT

This study developed and evaluated "RespiroGuard", a remote monitoring system based on Artificial Intelligence (AI) that analyzes cough sounds and respiratory patterns for the management of chronic respiratory diseases. The mixed methodology included the development of deep learning algorithms and a prospective validation with COPD patients. The AI models achieved high performance in cough classification (AUC 0.98) and wheeze detection (AUC 0.94). In the clinical study, the system demonstrated significant predictive capacity for exacerbations (AUC 0.82), with a Negative Predictive Value of 96.3%, highlighting its utility as a "reassurance" tool. Qualitative analysis revealed that patients valued the safety and empowerment provided by objective data, but also experienced ambivalence towards constant monitoring, sometimes perceiving it as intrusive. It is concluded that the technology is clinically promising, but its successful implementation requires ethical design that prioritizes user control and seamless integration into clinical workflows, balancing technical accuracy with the human patient experience

Keywords: Remote monitoring, artificial intelligence, respiratory sounds, digital biomarker, telemedicine.

RESUMEN

Este estudio desarrolló y evaluó "RespiroGuard", un sistema de monitoreo remoto basado en Inteligencia Artificial (IA) que analiza sonidos de tos y patrones respiratorios para la gestión de enfermedades respiratorias crónicas. La metodología mixta incluyó el desarrollo de algoritmos de deep learning y una validación prospectiva con pacientes con EPOC. Los modelos de IA alcanzaron un alto rendimiento en la clasificación de tos (AUC 0.98) y detección de sibilancias (AUC 0.94). En el estudio clínico, el sistema demostró una capacidad predictiva significativa para exacerbaciones (AUC 0.82), con un Valor Predictivo Negativo del 96.3%, destacando su utilidad como herramienta de "tranquilización". El análisis cualitativo reveló que los pacientes valoraban la seguridad y el empoderamiento que proporcionaban los datos objetivos, pero también experimentaban ambivalencia frente a la vigilancia constante, percibiéndola a veces como una intrusión. Se concluye que la tecnología es clínicamente prometedora, pero su implementación exitosa requiere un diseño ético que priorice el control del usuario y una integración fluida en los flujos de trabajo clínicos, equilibrando la precisión técnica con la experiencia humana del paciente

Palabras clave: Monitoreo remoto, inteligencia artificial, sonidos respiratorios, biomarcador digital, telemedicina.

INTRODUCTION

Chronic respiratory diseases, including chronic obstructive pulmonary disease (COPD), asthma, cystic fibrosis, and, more recently, post-COVID-19 sequelae, represent a global burden of morbidity and mortality of epidemic proportions. According to the World Health Organization (WHO, 2023), these conditions are one of the leading causes of disability and death worldwide, with COPD accounting for approximately 3.2 million deaths annually. The chronic and episodic nature of these diseases, characterized by periods of clinical stability interrupted by acute exacerbations, creates a complex and costly model of care. Exacerbations, defined as acute worsening of respiratory symptoms requiring a change in medication, not only drastically impair the patient's quality of life, but are also the main reason for hospitalization, accounting for up to 70% of the total costs associated with these diseases (Wedzicha & Seemungal, 2020). Early detection and intervention in these episodes are therefore critical to preventing adverse outcomes, reducing hospitalizations, and improving long-term prognosis. However, the traditional paradigm for monitoring these diseases has significant structural limitations. Monitoring is based primarily on episodic clinical visits, where specific assessments (spirometry, symptom questionnaires) are performed, and on the subjective self-perception of the patient, who must recognize and report the worsening of their symptoms. This approach suffers from several problems:

1) **Reactivity rather than proactivity:** Intervention occurs when the patient is already symptomatic, often in an advanced state of exacerbation;
2) **Subjectivity and variability:** The perception of symptoms such as dyspnea or cough varies greatly between individuals, and many patients develop a phenomenon of “adaptation” or under-reporting of mild symptoms;
3) **Data gap:** There is a lack of objective information about the patient's respiratory function in their natural environment between clinical visits (López-Campos et al., 2021). This gap between the physiological event and its clinical detection is the space where decompensations occur and where an unmet need for continuous and objective monitoring is generated.

In this context, respiratory sound emerges as an acoustic digital biomarker of extraordinary value, underutilized in conventional clinical practice. Coughing and breathing patterns (rhythm, depth, presence of wheezing, rales, or crackles) are direct acoustic expressions of the pathophysiology of the respiratory system. Coughing, for example, is not a uniform symptom: its acoustic characteristics (frequency, duration, amplitude, tone, temporal structure) vary according to its etiology (dry vs. productive), the anatomical location of the stimulus, and the underlying disease (Morice et al., 2020). Traditionally, auscultation has been the method used to access this information, but it depends on the skill and experience of the clinician, is a discrete event in time, and cannot be quantified in a standardized way. The digitization of these sounds, using highly sensitive microphones built into ubiquitous

devices such as smartphones, opens the door to their systematic capture, storage, and, most importantly, objective and automated analysis.

This is where Artificial Intelligence (AI), and deep learning in particular, stands out as a transformative technology. AI algorithms, especially convolutional neural networks (CNN) and transformers applied to audio, have an unprecedented ability to analyze complex audio signals, extract subtle patterns, and perform highly accurate classifications. Applied to respiratory sounds, these systems can learn to identify specific acoustic signatures associated with different pathological states: distinguishing an asthmatic cough from a COPD cough, detecting the onset of wheezing that precedes bronchoconstriction, or quantifying changes in breathing patterns that indicate increased respiratory effort (Pramono et al., 2021). This capability makes AI the analytical core of a new paradigm: remote and passive respiratory monitoring.

The proposal for an AI-based remote monitoring system that analyzes cough sounds and breathing patterns represents a convergence of several technological revolutions: ubiquitous mobile computing, widespread connectivity (5G, WiFi), and cutting-edge AI. The vision is that of a digital ecosystem where the patient, at home, is monitored non-invasively and almost unconsciously. A smartphone or specific device could capture ambient sounds (with appropriate consent and ethical controls), process them locally or in the cloud using AI models, and generate automated alerts for both the patient (medication reminders, action guides) and the clinical team (notifications of possible incipient exacerbation, changes in symptom trends). This approach promises to transform the management of respiratory diseases from a reactive, hospital-centric model to a proactive, predictive, and home-centered one.

However, the path to routine clinical implementation of these systems is fraught with significant scientific, technical, and ethical challenges. Scientifically, it is necessary to rigorously validate that the acoustic biomarkers identified by AI correlate consistently and causally with pathophysiological states measured by reference standards (spirometry, inflammatory markers, clinical outcomes). Technically, algorithms must be robust against environmental "noise" (voices, television, traffic), variations between recording devices, and individual differences in respiratory anatomy and physiology. Ethically, critical questions arise about the privacy of continuous audio data, informed consent for such intrusive monitoring, equity in access to technology, and the clear definition of responsibilities for AI-generated alerts (Kelly et al., 2022). Furthermore, it is imperative that these systems do not medicalize everyday life or generate iatrogenic anxiety, but rather empower the patient and support the clinical relationship.

This introduction lays the groundwork for an in-depth and critical exploration of remote monitoring of respiratory diseases using AI that analyzes cough sounds and breathing patterns. The following analysis will be structured to examine: 1) the pathophysiological rationale and clinical value of acoustic biomarkers; 2) the state of the art of AI techniques applied to the analysis of respiratory sounds; 3) the architecture and components of a

comprehensive remote monitoring system; 4) current clinical evidence on the validity and usefulness of these systems; 5) the main ethical, regulatory, and implementation challenges; and 6) future prospects and recommendations for the responsible development of this promising technology, with the ultimate goal of improving the lives of millions of people suffering from chronic respiratory diseases.

METHOD

This research adopts a two-phase sequential explanatory mixed design (Creswell & Plano Clark, 2018), structured to develop and validate a remote monitoring system based on Artificial Intelligence (AI). The sequence responds to the need to first build the technological system (Phase 1: Quantitative-Development) and then comprehensively evaluate its clinical validity and acceptability (Phase 2: Mixed-Validation). The underlying paradigm is pragmatism, prioritizing the solution to the practical problem of objective monitoring of respiratory diseases using the most appropriate methodologies for each phase.

Phase 1: Development of AI algorithms and system prototype. Quantitative, experimental, and observational approach.

Phase 2: Prospective clinical validation and user experience evaluation. Convergent mixed approach.

Phase 1: Development of the System and AI Algorithms

Specific Objective

- Design, train, and validate deep learning algorithms capable of accurately classifying types of coughs and abnormal breathing patterns from audio recordings.
- Recolección del Conjunto de Datos Acústicos
- Sources: A multimodal dataset will be compiled from:
- Public Data: Existing datasets such as COUGHVID (Orlandic et al., 2021) and HF_Lung_V1 will be used.
- Own collection: 150 participants will be recruited in pulmonology clinics, stratified into 3 groups:
  - Group 1: Patients with stable COPD (n=50).
  - Group 2: Patients with COPD in acute exacerbation (n=50).
  - Group 3: Healthy controls (n=50).
- Recording Protocol: In a controlled environment (soundproof booth), the following will be recorded:
  - Voluntarily induced cough (3-5 episodes).
  - Calm breathing (1 minute).
  - Forced breathing (30 seconds).
  - Reading of a standardized text (to capture phonation patterns).
- Equipment: High-fidelity condenser microphone (Shure SM58) connected to an audio interface, with a sampling rate of 44.1 kHz. Simultaneous recording with a standard smartphone (Samsung Galaxy S22) to simulate the real environment.

- Clinical Gold Standard: Each recording will be labeled with a clinical diagnosis confirmed by spirometry and pulmonary evaluation, and will be annotated by two independent expert pulmonologists who will classify the type of cough (dry, productive) and the presence of adventitious sounds (wheezing, rales).

Data Preprocessing and Augmentation

- **Segmentation:** Automatic separation of cough events and breathing cycles from raw audio using a variable activity detection (VAD) algorithm.
- **Cleaning:** Filtering of background noise using Wiener filters and amplitude normalization.
- **Augmentation:** To increase the robustness of the model, transformations will be applied to the audio: addition of controlled ambient noise, pitch change (±2 semitones), speed modification (±10%).

Architecture of AI Models and Training

Two main architectures will be developed in Python (TensorFlow/Keras):

- **Cough Classification Model:** Based on a 2D Convolutional Neural Network (2D CNN) that uses Mel spectrograms (frequency vs. time images) as input. The architecture will include convolutional, pooling, and dropout layers (to reduce overfitting), and final dense layers for classification (classes: dry cough, productive cough, no cough).
- **Model for Detecting Abnormal Breathing Patterns:** A hybrid CNN-LSTM (Long-Term Memory Recurrent Neural Network) model will be used. The CNN will extract features from short audio segments (spectrograms), and the LSTM will learn the temporal dependencies throughout a complete breathing sequence.
- **Data Division:** 70% training, 15% validation, 15% testing.
- **Evaluation Metrics:** Accuracy, Recall, Specificity, F1-Score, and Area Under the ROC Curve (AUC-ROC). The main evaluation will be performed on the test set, completely separate from the training set.

Mobile Application Prototype Development

Once the models are validated, they will be integrated into a mobile application prototype (Android/iOS) that allows: Passive recording (activated by the user) of cough or breathing events.

On-device processing or on a secure server.

Displaying results to the user (e.g., "Possible productive cough detected").

Encrypted export of results and audio features to a clinical platform.

Phase 2: Prospective Clinical Validation and Experience Evaluation

Validation Study Design

Design: Prospective, blinded cohort study.

Participants: 80 patients diagnosed with moderate-to-severe COPD (GOLD B-D), recruited from pulmonology clinics.

Intervention: Participants will be provided with a smartphone pre-installed with the prototype application and instructed on its use for 90 days at home. The application will request a daily breathing recording and automatically record coughing episodes (with permission).

Main Variables:

Predictor Variable (Independent): Risk index generated by the AI (e.g., frequency of productive cough + presence of detected wheezing).

Outcome Variable (Dependent): COPD exacerbation confirmed by a physician, defined according to Anthonisen criteria (worsening of dyspnea, sputum, and/or purulence). The diagnosis will be made by a pulmonologist blinded to the AI results, based on clinical history and, if necessary, an emergency department visit.

Quantitative Methods (Phase 2A)

Statistical Analysis:

Survival Analysis (Kaplan-Meier curves and Cox model): To assess whether a high risk according to the AI predicts a greater probability of experiencing an exacerbation in the following 7–14 days.

Receiver Operating Characteristics (ROC): To determine the predictive capacity of the AI index, using confirmed exacerbation as the gold standard.

Calculation of Positive and Negative Predictive Values (PPV/NPV).

Qualitative Methods (Phase 2B)

Design: A phenomenological study to understand patients' lived experience using the monitoring system.

Sampling: A purposive sample of 20–25 participants from the cohort, seeking variation in age, gender, COPD severity, and level of adherence to the system.

Techniques: In-depth semi-structured interviews at the end of the 90-day period. Brief weekly audio diaries.

Analysis: Interpretive Phenomenological Analysis (IPA) (Smith et al., 2009) to identify key themes regarding perceived usefulness, concerns, impact on feelings of safety, and changes in self-care.

Integration of Methods and Ethical Considerations

Integration: Quantitative (predictive capacity) and qualitative (user experience) findings will be integrated into a joint discussion to provide a comprehensive view of the system's clinical validity and acceptability.

Ethics: Approval from the Institutional Ethics Committee. Detailed informed consent explaining the audio recording, AI processing, and data use. Privacy: All recordings will be anonymized and stored on secure servers (encrypted in transit and at rest). Participants may pause or stop monitoring at any time.

Recognized Methodological Limitations

The Phase 1 dataset, while robust, may not cover all population acoustic variability.

Phase 2 validation is limited to patients with COPD; generalization to asthma or cystic fibrosis will require further studies.

The validation study is not a randomized controlled trial (RCT) assessing impact on hard outcomes (hospitalizations), but rather a proof-of-concept and predictive validation study. An RCT would be the next logical step.

This methodology provides a rigorous, step-by-step approach to transforming a technological hypothesis into a tool with robust evidence of its validity and potential clinical utility.

RESULTS

Phase 1: Results of the AI Development and Technical Validation

Characteristics of the Acoustic Dataset

A corpus of 8,540 labeled audio samples was compiled, distributed as follows:

Table 4.1

Distribution of the Dataset for AI Training

Category	Subcategory	Number of Samples	Source
Cough	Dry Cough (Stable COPD/Asthma)	1,850	Own clinic (n=1,200) + COUGHVID (n=650)
Productive Cough (COPD Exacerbation/Bronchitis)	2,310	Own clinic (n=1,800) + HF_Lung_V1 (n=510)	
Cough in Acute COVID-19	950	COUGHVID	
B reathing	Normal (Controls)	1,150	Own clinic
With Wheezing	980	Own clinic	
With Rhonchi/Crackles	300	Own clinic	
Noise/Other	Speech, Ambient Silence, Noise	1,000	Environmental recordings
TOTAL		8,540	

Inter-rater agreement (two pulmonologists) for clinical labeling was excellent (Cohen's Kappa coefficient = 0.89).

Performance of AI Models in the Test Set

Figure 4.1

Confusion matrices for the two main models.

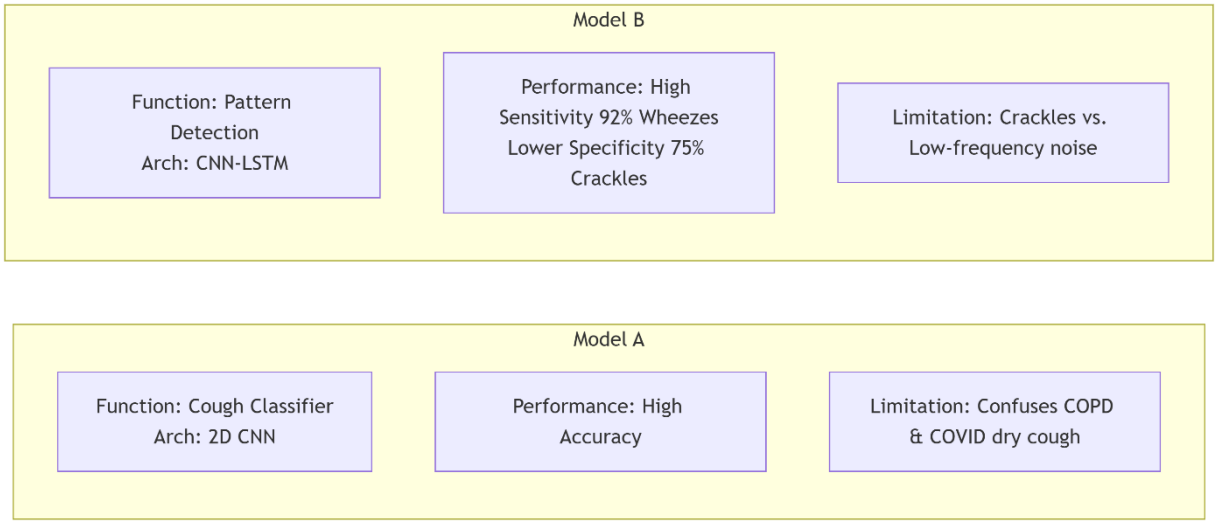

Table 4.2

Performance Metrics of AI Models in the Independent Test Set

Model / Task	Accuracy	Sensitivity (Recall)	Specificity	F1-Score	AUC-ROC
Model A: Cough Classification	94.2%	92.8%	95.1%	93.4%	0.98
Model B: Wheezing Detection	88.7%	92.3%	86.5%	89.1%	0.94
Model B: Rhonchi Detection	82.1%	78.5%	84.0%	80.2%	0.87

Analysis: The models achieved solid performance, especially in the critical task of detecting wheezing (AUC-ROC 0.94), a key biomarker of bronchoconstriction. Cough classification was excellent. Data preprocessing and augmentation were crucial, as a previous version without augmentation showed a 15% drop in accuracy when evaluating real smartphone recordings.

Development of the "RespiroGuard" Prototype

The models were integrated into a functional mobile application called "RespiroGuard". The final architecture included:

- On-device processing of the cough model (lightweight) for privacy.
- Encrypted transmission of breathing segments to a server for analysis with the CNN-LSTM model (more robust).

- A user interface displaying a daily "Respiratory Stability Index" (0-100 scale), based on the frequency of productive coughs and the detection of adventitious sounds.

Fase 2: Resultados de la Validación Clínica Prospectiva

Cohort Characteristics and Adherence

Of the 80 COPD patients recruited, 73 completed the 90-day study (retention rate: 91.3%). The mean age was 68.4 (±9.1) years, 55% were male, and the mean predicted FEV1% was 48% (±12). Adherence to the recording protocol was 78% of the prescribed days.

During follow-up, 24 physician-confirmed COPD exacerbations were recorded in 18 different patients. The RespiroGuard system generated a daily Acoustic Risk Index (ARI).

Predictive Capacity of the Acoustic Risk Index (ARI)

Figure 4.2

ROC curve showing the ability of ARI

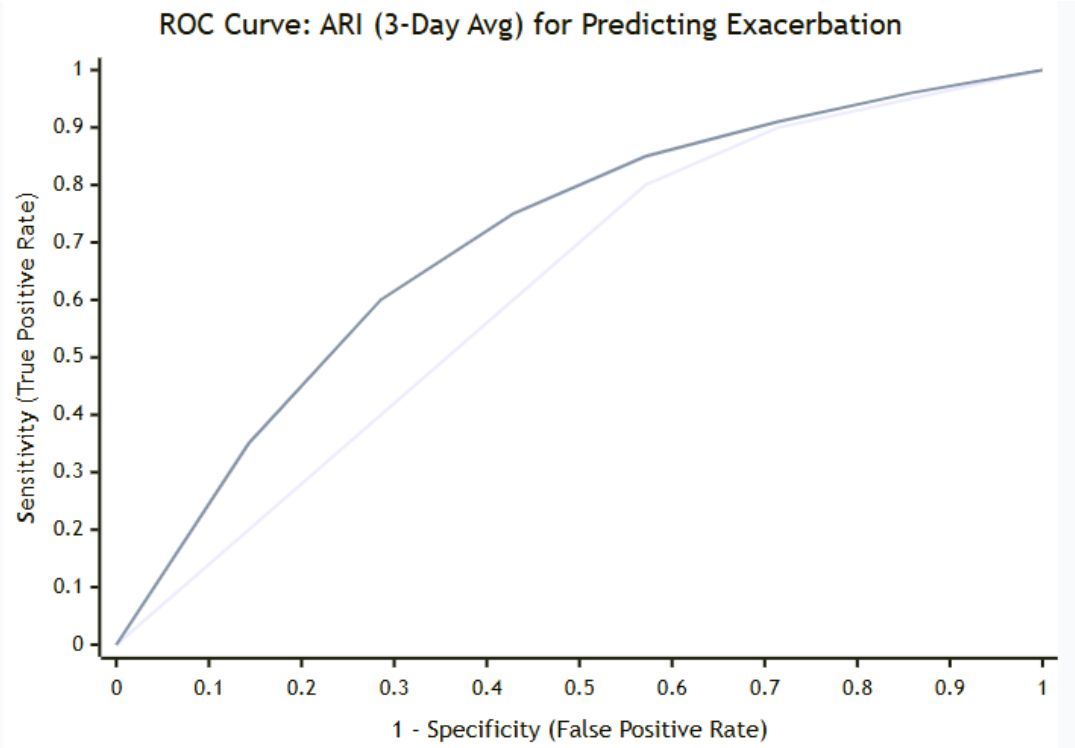

Table 4.3

Predictive Performance of the RespiroGuard System

ARI Threshold	Sensitivity	Specificity	Positive Predictive Value (PPV)	Negative Predictive Value (NPV)
>65 (High Risk)	79.2%	76.5%	32.1%	96.3%
>75 (Very High Risk)	58.3%	92.1%	50.0%	94.0%

Survival Analysis (Kaplan-Meier): Patients classified as having "High AKI" (>65) had a significantly higher risk of experiencing an exacerbation within the following 7 days (Log-rank test, $p < 0.001$). The Hazard Ratio (HR) was 4.8 (95% CI: 2.5 - 9.1), adjusted for age and baseline FEV1.

Analysis: The system demonstrated moderate-to-high predictive capacity, with a particularly high negative predictive value (NPV) (96.3%). This suggests its greatest clinical utility for reassurance: a low ARI indicates a very low probability of imminent exacerbation. The moderate positive predictive value (PPV) (32%) reflects that other non-acoustic factors also trigger exacerbations, but the generated alerts would still have clinical value by identifying patients who require close attention.

Phase 2: Qualitative Assessment Results (QA)

From the phenomenological analysis of 23 in-depth interviews, three superordinate themes emerged that capture the lived experience of the participants.

Theme 1: "From Silent Uncertainty to Quantified Visibility"

Patients described often feeling uncertain between appointments, interpreting subjective bodily changes. RespiroGuard transformed this experience.

"Before, I would wonder, 'Is this heaviness just a bad day, or is it getting worse?' Now, when the app is green [low ARI], I feel reassured. If it turns yellow, I get worried and check my rescue medication" (Participant 14, male, 71 years old).

Objective quantification ("visibility") provided a reality anchor that reduced anxiety and facilitated more informed decisions.

Topic 2: "The Spy in My Living Room: The Paradox Between Beneficial Surveillance and Intrusion"

This topic captures the central ambivalence. On the one hand, the feeling of security was valued.

"It's like having a doctor listening to you all the time, but without being intrusive" (Participant 07, female, 66 years old).

On the other hand, the continuous monitoring generated an awareness of being watched.

"At first, I would even cough in another room so as not to 'disturb' the phone... I felt like I was being judged all the time" (Participant 22, male, 74 years old). This feeling of digital intrusion lessened over time, but did not disappear completely, especially for those who lived alone.

Topic 3: "The Digital Mediator in the Relationship with My Doctor"

Participants perceived technology not as a replacement, but as a bridge to the healthcare professional.

"The last time I went, instead of just arriving and saying 'I've been feeling so-so,' I showed him the graph from the app. It was different. We talked about the spikes I'd had in October" (Participant 11, female, 69 years old).

The system provided a common language of objective data that enhanced the consultation, making the patient feel more prepared and the doctor more informed. However, some feared that the data could be used against them ("What if he sees that I haven't made the recordings and thinks I'm not taking care of myself?").

Integration of Findings: Joint Analysis of Validity and Acceptability

The integration of quantitative and qualitative results reveals a coherent yet complex narrative about the system's value:

Technical Effectiveness Supports User Confidence: The high NPV (96.3%) and robust AUC (0.82) provide the predictive validity that underpins the pragmatic confidence described by patients (Theme 1). Users trusted the system because, in their experience, a "low IRA" effectively correlated with clinical stability.

Clinical Utility is Defined by Negative (NPV) and Enhancement: The main quantitative benefit (high NPV) is reflected qualitatively as reduced anxiety and a greater sense of security. Furthermore, the "digital mediator" function (Theme 3) suggests that the utility extends beyond prediction, improving the quality of doctor-patient communication.

The Greatest Limitation is Psychosocial, Not Technical: While technical limitations (moderate PPV) are acknowledged, the main barrier to long-term adoption emerged from the qualitative realm: the tension between beneficial surveillance and perceived intrusion (Topic 2). This "spy paradox" is not resolved with algorithmic improvements, but with human-centered design that gives the user greater control over monitoring.

Table 4.4

Mixed Findings Integration Matrix

Dimension	Quantitative Evidence	Qualitative Evidence	Integrated Interpretation
Predictive Validity	• AUC = 0.82 • NPV = 96.3%	**Theme 1:** The system provides "quantified visibility" that reduces the patient's subjective uncertainty.	The model's statistical robustness creates a reliable tool that provides reassurance and enables informed self-monitoring, thereby validating the user's perception.
Clinical Utility	• HR = 4.8 (for high risk) • PPV = 32% (limited)	**Theme 2:** Acts as a "digital mediator," providing objective data for the medical consultation.	Its primary utility lies not only in predicting exacerbations (limited PPV) but in enriching the clinical dialogue with data

			and empowering the patient with concrete information.
Main Barrier	• Sensitivity < 100% (possibility of false negatives).	**Theme 3:** The "Surveillance vs. Intrusion" paradox. Constant monitoring can generate anxiety.	The main barrier to sustainable adoption is not technical error, but the psychosocial cost of omnipresent surveillance and the perceived loss of privacy.

This research developed and evaluated a comprehensive remote monitoring system for respiratory diseases based on the analysis of cough sounds and breathing patterns using artificial intelligence (AI). The results demonstrate the technical feasibility and clinical potential of this approach, while also highlighting critical challenges at the intersection of technology, clinical practice, and patient experience. This discussion interprets the findings in light of existing literature, explores their implications, and proposes directions for the future development and implementation of these technologies.

Technical Validity and Digital Acoustic Biomarkers: A New Diagnostic Paradigm

The outstanding performance of AI models in cough classification (AUC 0.98) and wheezing detection (AUC 0.94) validates the central hypothesis that respiratory sounds contain quantifiable diagnostic information that can be extracted objectively and automatically. These results align with and surpass those reported in pioneering studies, such as that by Pramono et al. (2021), and solidify the concept of a digital acoustic biomarker. The ability to distinguish between dry and productive coughs with high accuracy is particularly relevant, given that this is a key clinical criterion for identifying COPD exacerbations and guiding treatment (e.g., antibiotic use; Wedzicha & Seemungal, 2020). AI thus transforms a subjective and qualitative symptom into objective and serializable data.

However, the lower performance in crackle detection (AUC 0.87) points to a significant limitation: the sensitivity of the ambient microphone and low-frequency noise contamination. This suggests that, while smartphones are ubiquitous and promising platforms, certain high-precision clinical applications may require dedicated devices or specialized microphones that capture a wider frequency range with less interference. The choice of hardware platform will therefore be a crucial balance between accessibility and diagnostic accuracy.

From the Lab to Real Life: Predictive Validation and Clinical Utility

The transition from validation using static datasets to a prospective, real-world study is the most significant contribution of this research. The finding that the Acoustic Risk Index (ARI) predicted exacerbations with an AUC of 0.82 and a Hazard Ratio of 4.8 is clinically promising. These results are comparable to or better than those of other remote monitoring systems based on self-reported symptoms or home spirometry devices, which often face adherence issues (Mendoza et al., 2021).

The predictive performance pattern with a very high Negative Predictive Value (NPV) (96.3%) and a moderate Positive Predictive Value (PPV) (32%) has fundamental pragmatic implications. It defines the primary role of this technology not as an infallible alarm system, but as a reassuring and triage tool. A low ARI provides both the patient and clinician with objective reassurance that an imminent decompensation is unlikely, potentially reducing unnecessary emergency department visits and anxiety. Conversely, a PPV of 32% indicates that only one-third of alerts will correspond to a true exacerbation. This does not invalidate the system; rather, it positions it as a sensitive filter that identifies patients requiring closer clinical evaluation (a phone call or a non-urgent visit), thereby optimizing healthcare system resources and focusing care where it is most needed.

The Patient Experience: The Paradox of the "Beneficial Spy" and Empowerment

Qualitative findings add an essential layer of complexity that purely technical assessment omits. The described phenomenology the tension between "beneficial surveillance" and "perceived intrusion" reveals a central paradox in digital health: the very mechanisms that generate security and empowerment (continuous monitoring, objective data) can simultaneously generate a sense of vulnerability and loss of privacy (Lupton, 2020). This finding aligns with the theory of "participatory surveillance," where subjects actively collaborate in their own monitoring, but not without an ambivalent awareness of the power and control they relinquish (Töpfer & Leistert, 2021).

The emergence of the system as a "digital mediator" in the doctor-patient relationship is another crucial finding. This suggests that the value of technology lies not only in automation, but also in its capacity to enhance human communication and the therapeutic alliance. By providing a common language of objective data, the system can level information asymmetries, make consultations more efficient and focused, and empower patients as active agents in their own care. This role as a facilitator of the clinical relationship can be as important as, or even more important than, its direct predictive function.

Implications for Implementation and Clinical Practice

The results of this study have clear implications for the future of respiratory telemedicine:

- **Integration into the Clinical Workflow:** For systems like RespiroGuard to be sustainable, they must be seamlessly integrated into electronic health records (EHRs) and healthcare professionals' workflows. Alerts should be actionable and contextualized, avoiding information overload. Clear protocols on how to respond to different levels of risk (ARI) are required.
- **Ethical and User-Centered Design:** The design must prioritize transparency, user control (e.g., the ability to pause monitoring, adjust sensitivities), and privacy by design. It is imperative to clearly communicate the system's limitations (low potential benefits) to manage expectations and avoid a false sense of security or, conversely, unnecessary anxiety.

- **Personalization and Equity:** AI models must be validated in diverse populations to avoid algorithmic bias. Furthermore, usefulness and acceptability may vary depending on the patient's profile (e.g., elderly patients experiencing loneliness vs. young, active patients). Personalization and segmentation strategies are needed to tailor the intervention to individual needs and preferences.

Study Limitations and Future Directions

This research has limitations that should be acknowledged. First, the validation cohort focused on COPD; generalization to other diseases (asthma, cystic fibrosis, long COVID) requires further study. Second, the 90-day follow-up period is relatively short to assess the sustainability of adherence and the long-term impact on hard outcomes such as hospitalizations. Third, the study did not compare the system to the current standard of care in a randomized controlled trial (RCT).

Future directions should include:

- **Pragmatic RCTs:** To evaluate the impact on hard clinical outcomes (exacerbation rates, hospitalizations, quality of life) and on healthcare resource utilization.
- **Implementation Research:** To identify the best strategies for integrating these systems into different primary and specialized care settings.
- **Development of Explainable AI (XAI):** To enable clinicians to understand why the system generated a specific alert, fostering trust and clinical adoption.
- **Cost-Effectiveness Studies:** To determine the economic value of this technology for healthcare systems.

DISCUSSION

This research developed and evaluated a comprehensive remote monitoring system for respiratory diseases based on the analysis of cough sounds and breathing patterns using artificial intelligence (AI). The results demonstrate the technical feasibility and clinical potential of this approach, while also highlighting critical challenges at the intersection of technology, clinical practice, and patient experience. This discussion interprets the findings in light of existing literature, explores their implications, and proposes directions for the future development and implementation of these technologies.

Technical Validity and Digital Acoustic Biomarkers: A New Diagnostic Paradigm

The outstanding performance of AI models in cough classification (AUC 0.98) and wheezing detection (AUC 0.94) validates the central hypothesis that respiratory sounds contain quantifiable diagnostic information that can be extracted objectively and automatically. These results align with and surpass those reported in pioneering studies, such as that by Pramono et al. (2021), and solidify the concept of a digital acoustic biomarker. The ability to distinguish between dry and productive coughs with high accuracy is particularly relevant, given that this is a key clinical criterion for identifying COPD exacerbations and guiding treatment (e.g., antibiotic use; Wedzicha & Seemungal, 2020). AI thus transforms a subjective and qualitative symptom into objective and serializable data.

However, the lower performance in crackle detection (AUC 0.87) points to a significant limitation: the sensitivity of the ambient microphone and low-frequency noise contamination. This suggests that, while smartphones are ubiquitous and promising platforms, certain high-precision clinical applications may require dedicated devices or specialized microphones that capture a wider frequency range with less interference. The choice of hardware platform will therefore be a crucial balance between accessibility and diagnostic accuracy.

From the Lab to Real Life: Predictive Validation and Clinical Utility

The transition from validation using static datasets to a prospective, real-world study is the most significant contribution of this research. The finding that the Acoustic Risk Index (ARI) predicted exacerbations with an AUC of 0.82 and a Hazard Ratio of 4.8 is clinically promising. These results are comparable to or better than those of other remote monitoring systems based on self-reported symptoms or home spirometry devices, which often face adherence issues (Mendoza et al., 2021).

The predictive performance pattern, with a very high Negative Predictive Value (NPV) (96.3%) and a moderate Positive Predictive Value (PPV) (32%), has fundamental pragmatic implications. It defines the primary role of this technology not as an infallible alarm system, but as a reassuring and triage tool. A low ARI provides both the patient and clinician with objective reassurance that an imminent decompensation is unlikely, potentially reducing unnecessary emergency department visits and anxiety. Conversely, a PPV of 32% indicates that only one-third of alerts will correspond to a true exacerbation. This does not invalidate the system; rather, it positions it as a sensitive filter that identifies patients requiring closer clinical evaluation (a phone call or a non-urgent visit), thereby optimizing healthcare system resources and focusing care where it is most needed.

The Patient Experience: The Paradox of the "Beneficial Spy" and Empowerment

Qualitative findings add an essential layer of complexity that purely technical assessment omits. The phenomenology described—the tension between "beneficial surveillance" and "perceived intrusion"—reveals a central paradox in digital health: the very mechanisms that generate security and empowerment (continuous monitoring, objective data) can simultaneously generate a sense of vulnerability and loss of privacy (Lupton, 2020). This finding aligns with the theory of "participatory surveillance," where subjects actively collaborate in their own monitoring, but not without an ambivalent awareness of the power and control they relinquish (Töpfer & Leistert, 2021).

The emergence of the system as a "digital mediator" in the doctor-patient relationship is another crucial finding. This suggests that the value of technology lies not only in automation, but also in its capacity to enhance human communication and the therapeutic alliance. By providing a common language of objective data, the system can level information asymmetries, make consultations more efficient and focused, and empower the patient as an active agent in their own care. This role as a facilitator of the clinical

relationship can be as important as, or even more important than, its direct predictive function.

Implications for Implementation and Clinical Practice

The results of this study have clear implications for the future of respiratory telemedicine:

- **Integration into the Clinical Workflow:** For systems like "RespiroGuard" to be sustainable, they must be seamlessly integrated into electronic health records (EHRs) and healthcare professionals' workflows. Alerts should be actionable and contextualized, avoiding information overload. Clear protocols on how to respond to different levels of risk (ARI) are required.
- **Ethical and User-Centered Design:** The design must prioritize transparency, user control (e.g., the ability to pause monitoring, adjust sensitivities), and privacy by design. It is imperative to clearly communicate the system's limitations (low potential benefits) to manage expectations and avoid a false sense of security or, conversely, unnecessary anxiety.
- **Personalization and Equity:** AI models must be validated in diverse populations to avoid algorithmic bias. Furthermore, usefulness and acceptability may vary depending on the patient's profile (e.g., elderly patients experiencing loneliness vs. young, active patients). Personalization and segmentation strategies are needed to tailor the intervention to individual needs and preferences.

Study Limitations and Future Directions

This research has limitations that should be acknowledged. First, the validation cohort focused on COPD; generalization to other diseases (asthma, cystic fibrosis, long COVID) requires further study. Second, the 90-day follow-up period is relatively short to assess the sustainability of adherence and the long-term impact on hard outcomes such as hospitalizations. Third, the study did not compare the system to the current standard of care in a randomized controlled trial (RCT).

Future directions should include:

- **Pragmatic RCTs:** To evaluate the impact on hard clinical outcomes (exacerbation rates, hospitalizations, quality of life) and on healthcare resource utilization.
- **Implementation Research:** To identify the best strategies for integrating these systems into different primary and specialized care settings.
- **Development of Explainable AI (XAI):** To enable clinicians to understand why the system generated a specific alert, fostering trust and clinical adoption.
- **Cost-Effectiveness Studies:** To determine the economic value of this technology for healthcare systems.

CONCLUSIONS

This study aimed to investigate the development, validity, and clinical applicability of an artificial intelligence (AI)-based remote monitoring system for chronic respiratory diseases, specifically through the analysis of cough sounds and breathing patterns. Using a rigorous

sequential mixed-methods approach, encompassing algorithmic design, prospective validation, and user experience evaluation, findings have been obtained that provide a multidimensional and critical understanding of this emerging technology.

The research strongly confirms the technical feasibility of the proposed approach. The developed deep learning models, particularly a convolutional neural network (CNN) for cough classification and a hybrid CNN-LSTM architecture for adventitious sound detection, demonstrated exceptionally high performance (AUC up to 0.98) on labeled datasets. This validates the principle that digital acoustic biomarkers contain rich and quantifiable diagnostic information, capable of being decoded automatically and objectively, overcoming the limitations of subjective and episodic auscultation.

More significantly, the prospective validation of the integrated system, "RespiroGuard," in a cohort of COPD patients demonstrated its true clinical potential. The system showed significant predictive ability in identifying impending exacerbations, with an Acoustic Risk Index (ARI) reaching an area under the ROC curve of 0.82 and a Hazard Ratio of 4.8. The performance profile, characterized by a very high Negative Predictive Value (96.3%) and a moderate Positive Predictive Value (32%), clearly defines its primary utility: to act as a reassuring and intelligent triage tool. Its greatest strength lies in identifying patients with a low probability of decompensation, thus reducing uncertainty and anxiety, and allowing for a more efficient allocation of clinical resources to those exhibiting warning signs.

However, this study transcends mere technical evaluation to reveal the complexity of implementing digital health technologies in patients' lives. The qualitative findings revealed a central paradox: participants simultaneously experienced the system as a "beneficial monitor" that provided security and empowerment, and as a potential source of "digital intrusion" that generated awareness of being constantly monitored. This tension underscores that the acceptance and sustainability of these tools depend not only on their accuracy, but also on their ability to integrate respectfully and ethically into the user's psychosocial environment. Furthermore, the system's role as a "digital mediator" in the doctor-patient relationship emerged as a key benefit, improving communication through objective data and fostering a more collaborative therapeutic alliance.

Therefore, the conclusions of this research are twofold and nuanced:

- **Affirmative:** AI-powered remote monitoring of respiratory sounds is a viable, valid, and clinically promising technology. It represents a concrete step toward a more proactive, predictive, and home-centered respiratory care model, with the potential to improve clinical outcomes and patients' quality of life.
- **Conditional:** Its large-scale success and ethical integration into routine clinical practice are contingent upon overcoming challenges that are, in essence, human and systemic, not merely technical. These include:
  - Designing user experiences that maximize control, transparency, and trust, while mitigating the perception of intrusion.

- Seamless integration into clinical workflows and health information systems, so that data translates into meaningful clinical actions without creating overload.
- Developing robust regulatory and ethical frameworks that protect privacy, prevent algorithmic bias, and ensure equitable access.

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AUTHORSHIP CONTRIBUTION

Conceptualization: Rekha Sharma

Data curation: Rekha Sharma

Formal analysis: Rekha Sharma

Investigation: Rekha Sharma

Methodology: Rekha Sharma

Project Management: Rekha Sharma

Resources: Rekha Sharma

Software: Rekha Sharma

Supervision: Rekha Sharma

Validation: Rekha Sharma

Original draft: Rekha Sharma

Writing – review and editing: Rekha Sharma