JHWCR JOURNAL OF HEALTH, WELLNESS AND COMMUNITY RESEARCH 3007-0570

https://doi.org/10.61919/275sd873

Original Article

AI-Driven Screening of Undiagnosed Chronic Respiratory Disorders in Smokers Visiting Public Clinics

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"Cite this Article" Received: 11 January 2026; **Accepted**: 17 April 2026; **Published**: 08 May 2026

Author Contributions: Concept: ZN; Design: KA and SNE; Data Collection: FN, MS, and ZS; Analysis: IQ; Drafting: ZN, KA, and SNE. **Ethical Approval**: National Institute of Medical Sciences, Rawalpindi, Pakistan. **Informed Consent**: Written informed consent was obtained from all participants; **Conflict of Interest**: The authors declare no conflict of interest. **Funding**: No external funding; **Data Availability**: Available from the corresponding author on reasonable request; **Acknowledgments**: N/A.

ABSTRACT

Background: Chronic respiratory diseases remain underdiagnosed among smokers, particularly in resource-limited public healthcare settings where routine spirometry is not consistently available. Artificial intelligence-supported screening may improve early identification of high-risk individuals requiring confirmatory evaluation. Objective: To evaluate the diagnostic accuracy of an AI-supported screening tool for detecting undiagnosed chronic respiratory disease among smokers attending urban public clinics in Lahore, Pakistan. Methods: This cross-sectional diagnostic accuracy study included 500 adult current or former smokers aged 35–70 years with at least 10 pack-years of exposure and no prior chronic respiratory disease diagnosis. Participants underwent AI-supported screening using demographic, smoking-related, clinical, symptom, pulse oximetry, and digital auscultation variables, followed by post-bronchodilator spirometry as the reference standard. Diagnostic performance was assessed using sensitivity, specificity, predictive values, overall accuracy, ROC analysis, calibration testing, and Cohen's kappa agreement. Results: Spirometry confirmed chronic respiratory disease in 160 participants (32.0%). The AI tool correctly identified 130 true-positive and 240 true-negative cases, with 30 false negatives and 40 false positives. Overall accuracy was 88.0%, sensitivity 81.3%, specificity 85.7%, positive predictive value 76.5%, and negative predictive value 88.9%. The AUC was 0.91, Cohen's kappa was 0.78, and the Hosmer–Lemeshow p-value was 0.41. Conclusion: AI-supported screening showed high diagnostic accuracy and substantial agreement with spirometry, supporting its potential role as a triage tool for early respiratory disease detection among smokers in public clinic settings. Keywords: Artificial Intelligence, Chronic Obstructive Pulmonary Disease, Early Diagnosis, Machine Learning, Pakistan, Pulmonary Function Tests, Smokers.

INTRODUCTION

Chronic respiratory diseases, particularly chronic obstructive pulmonary disease, asthma-related chronic airflow limitation, chronic bronchitis, bronchiectasis, and other smoking-associated pulmonary conditions, remain major contributors to preventable morbidity, disability, and premature mortality worldwide. Tobacco smoking is the most consistent and modifiable risk factor for chronic airway injury, yet a substantial proportion of smokers remain undiagnosed until airflow limitation, symptom burden, and functional impairment become clinically advanced. This diagnostic delay is especially important in primary care and public clinic settings, where high-risk smokers frequently present with cough, wheeze, sputum production, or exertional dyspnea but are often treated symptomatically without formal pulmonary function assessment. Although spirometry remains the standard diagnostic method for

confirming airflow obstruction, its routine use is limited in many low- and middle-income healthcare systems because of equipment availability, trained personnel requirements, time constraints, and inconsistent integration into outpatient workflows (1,2).

Smoking-related respiratory impairment often develops gradually, and early clinical manifestations may be nonspecific or normalized by patients as expected consequences of smoking. Previous studies have shown that cumulative tobacco exposure is strongly associated with COPD, chronic bronchitis, respiratory symptoms, and progressive decline in pulmonary function, while disease awareness among smokers remains low despite the presence of clinically relevant symptoms (3-6). This creates a persistent detection gap in which individuals at high risk are not identified until complications or advanced disease occur. In urban public clinics in Pakistan, this gap is likely amplified by heavy patient load, limited access to specialist respiratory assessment, low affordability of diagnostic testing, and competing priorities in primary care consultations. Therefore, scalable approaches that can identify smokers requiring confirmatory testing are urgently needed to improve early diagnosis and referral.

Artificial intelligence has emerged as a potentially useful strategy for respiratory risk stratification because machine-learning models can integrate demographic characteristics, smoking exposure, symptoms, physiological measurements, and digital clinical signals to generate individualized disease-risk predictions. Compared with conventional symptom-based screening alone, AI-supported tools may offer more consistent decision support, reduce dependence on specialist interpretation, and prioritize spirometry for patients most likely to have underlying chronic respiratory disease. AI methods have already shown promise in respiratory medicine through prediction models for COPD risk, asthma exacerbations, imaging-based disease classification, molecular biomarker discovery, and automated interpretation of multimodal clinical data (7-9). However, many existing models have been developed in hospital-based, imaging-rich, or high-resource settings, limiting their direct applicability to routine public clinic environments where only basic clinical and physiological inputs may be available.

The major knowledge gap is the limited validation of AI-supported screening tools for undiagnosed chronic respiratory disease among smokers in real-world, resource-limited primary care settings, particularly in Pakistan. Existing evidence supports the technical potential of AI, but fewer studies have evaluated whether such tools can function as practical screening aids in public outpatient clinics where spirometry is not routinely available for all high-risk individuals. Furthermore, diagnostic performance may vary according to local smoking patterns, symptom-reporting behavior, environmental exposures, healthcare access, and disease prevalence, making context-specific evaluation essential before implementation. Population-level smoker screening has been proposed as a more effective approach than symptom-triggered case finding alone, but broad implementation remains difficult without automated, low-cost, and reproducible triage systems (10-12).

Accordingly, the present study was conducted to evaluate the diagnostic accuracy and clinical utility of an AI-supported screening tool for identifying undiagnosed chronic respiratory disease among adult smokers attending urban public clinics in Lahore, Pakistan. By comparing AI-generated predictions against post-bronchodilator spirometry as the reference standard, the study aimed to determine whether AI-assisted screening could reliably detect likely chronic respiratory impairment in a high-risk population. The primary objective was to assess the sensitivity, specificity, predictive values, overall accuracy, and discriminative performance of the AI-supported tool, while the secondary objective was to evaluate agreement between AI classification and spirometric diagnosis. The study was guided by the research question: among adult smokers with no prior diagnosis of chronic respiratory disease, how accurately can an AI-supported clinical screening model identify undiagnosed chronic respiratory disease compared with confirmatory spirometry?

MATERIALS AND METHODS

This cross-sectional diagnostic accuracy study was conducted from January 2025 to August 2025 in selected urban public healthcare clinics in Lahore, Pakistan, to evaluate the performance of an artificial intelligence-supported screening tool for detecting undiagnosed chronic respiratory disease among smokers. The study design was selected because the primary aim was to compare an index screening test against a reference diagnostic standard at a single point of assessment. Adult clinic attendees were recruited consecutively from outpatient services serving predominantly lower- and middle-income urban populations. Eligible participants were current or former smokers aged 35 to 70 years with a smoking history of at least 10 pack-years and no previously established diagnosis of chronic respiratory disease, including COPD, asthma, interstitial lung disease, bronchiectasis, or chronic bronchitis. Participants were excluded if they had an acute respiratory infection at the time of assessment, recent thoracic surgery, active pulmonary tuberculosis, known pulmonary malignancy, unstable medical illness, or cognitive impairment that prevented reliable participation or informed consent.

Recruitment was performed during routine outpatient clinic visits by trained research staff who screened potential participants using a structured eligibility checklist. Written informed consent was obtained before enrollment, and participants were informed that AI-based screening was investigational and that abnormal findings would require clinical confirmation. Demographic data, smoking history, occupational exposure history, respiratory symptom profile, previous respiratory evaluations, comorbidities, and relevant clinical measurements were collected using standardized electronic data capture forms. Smoking exposure was operationalized as pack-years, calculated by multiplying the number of cigarette packs smoked per day by the number of years smoked. Respiratory symptoms included chronic cough, sputum production, wheeze, dyspnea, and exercise intolerance, recorded through interviewer-administered questions to reduce misclassification due to literacy variation. Physiological inputs included pulse oximetry and digital auscultation findings obtained using an electronic stethoscope under standardized room conditions.

The index test was an AI-supported diagnostic screening model designed to estimate the probability of chronic respiratory disease using demographic, clinical, smoking-related, symptomatic, and physiological variables. The model applied supervised machine-learning classification based on gradient-boosted decision trees, selected for its ability to handle nonlinear relationships and interactions among clinical predictors. Input variables included age, sex, smoking duration, pack-years, symptom profile, oxygen saturation, and digital auscultation features. Before analysis, data were checked for completeness, range validity, implausible values, and duplicate entries. The AI output categorized participants as “likely chronic respiratory disease,” “possible chronic respiratory disease,” or “no significant findings.” For primary diagnostic accuracy analysis, “likely” and clinically significant “possible” categories were binary-coded as screening positive when aligned with the prespecified probability threshold, while “no significant findings” was coded as screening negative. The final classification threshold was selected using receiver operating characteristic analysis and the Youden index to optimize the balance between sensitivity and specificity.

The reference standard was post-bronchodilator spirometry performed according to American Thoracic Society and European Respiratory Society quality standards. Spirometry was conducted by trained personnel using calibrated equipment, and participants received bronchodilator administration before repeat testing where indicated. Chronic obstructive pulmonary disease was defined by a post-bronchodilator FEV_1/FVC ratio of less than 0.70, while additional clinical information, chest radiography, and fractional exhaled nitric oxide testing were used to support identification of asthma-like or mixed respiratory patterns when clinically relevant (13-15). AI predictions were compared with reference-standard diagnostic classification after completion of clinical testing. To reduce review bias, spirometry interpretation was performed independently of the AI screening output wherever feasible, and AI classification was generated before final reference-standard adjudication.

The sample size was calculated for a diagnostic accuracy design using an expected AI-screening sensitivity of 85%, 95% confidence level, 5% absolute precision, and an anticipated prevalence of undiagnosed chronic respiratory disease of approximately 20% among smokers attending urban clinics. The minimum required sample size was estimated at 460 participants, and the final target sample was increased to 500 to compensate for incomplete assessments and potential exclusions after quality control. The primary outcome was diagnostic accuracy of the AI-supported screening tool, expressed as sensitivity, specificity, positive predictive value, negative predictive value, and overall accuracy. Secondary outcomes included the area under the receiver operating characteristic curve, optimal probability threshold, calibration performance, and agreement between AI classification and spirometry diagnosis using Cohen's kappa coefficient.

Statistical analysis was performed using IBM SPSS Statistics version 27. Continuous variables were summarized as mean and standard deviation, while categorical variables were reported as frequencies and percentages. Normality of continuous variables was assessed using histograms and the Shapiro-Wilk test. Diagnostic performance was calculated using a 2 × 2 contingency table comparing AI screening classification with spirometry-based diagnosis. Receiver operating characteristic analysis was used to estimate discriminative ability, and the optimal threshold was identified by maximizing the Youden index. Cohen's kappa was used to assess agreement beyond chance, and model calibration was assessed using the Hosmer-Lemeshow goodness-of-fit test. Subgroup performance analyses were planned according to age group, sex, and smoking intensity to evaluate stability of screening accuracy across clinically relevant strata. Potential confounding by age, sex, smoking intensity, occupational exposure, and comorbidity profile was considered during subgroup interpretation and sensitivity analysis. Missing or incomplete values were reviewed before analysis; records with missing primary diagnostic outcome data were excluded from diagnostic accuracy calculations, while incomplete non-primary variables were handled using complete-case analysis for the relevant comparison.

To assess internal robustness, five-fold cross-validation was performed, with each fold containing approximately 20% of the dataset while preserving balanced representation of diagnostic categories. Data integrity was maintained through standardized training of data collectors, weekly database checks, predefined coding rules, restricted access to identifiable records, and removal of personal identifiers before analysis. Ethical approval was obtained from the relevant institutional review board, and all procedures were conducted in accordance with the Declaration of Helsinki. Participants with abnormal spirometry or clinically concerning findings were counseled and referred for further respiratory evaluation and management. This methodological approach was intended to provide a reproducible and clinically grounded assessment of AI-assisted screening as a potential triage tool for undiagnosed chronic respiratory disease among smokers in public clinic settings.

RESULTS

A total of 500 adult smokers were included in the final diagnostic accuracy analysis. The mean age was 52.6 ± 8.7 years, and the sample included 310 males (62.0%) and 190 females (38.0%). The mean smoking duration was 24.3 ± 9.5 years, with a mean cumulative exposure of 28.7 ± 10.2 pack-years. The mean BMI was 26.1 ± 3.8 kg/m², and all participants were recruited from urban public clinic settings in Lahore. Respiratory symptoms were common, with chronic cough reported by 180 participants (36.0%), wheezing by 155 (31.0%), and dyspnea by 122 (24.4%). The AI-supported screening tool classified 160 participants (32.0%) as having likely chronic respiratory disease, 50 (10.0%) as having possible chronic respiratory disease, and 290 (58.0%) as having no significant findings.

Table 1. Baseline Demographic and Clinical Characteristics of Participants (n = 500)

Variable	Mean ± SD / n (%)
Age, years	52.6 ± 8.7
Male sex	310 (62.0%)
Female sex	190 (38.0%)

Variable	Mean ± SD / n (%)
Smoking duration, years	24.3 ± 9.5
Smoking exposure, pack-years	28.7 ± 10.2
BMI, kg/m²	26.1 ± 3.8
Urban residence	500 (100.0%)
Chronic cough	180 (36.0%)
Wheezing	155 (31.0%)
Dyspnea	122 (24.4%)

Spirometry confirmed chronic respiratory disease in 160 participants (32.0%). When AI classification was compared with spirometry, 130 cases were correctly identified as true positives and 240 participants were correctly identified as true negatives. The AI tool missed 30 spirometry-confirmed cases and misclassified 40 participants as false positives. This produced an overall accuracy of 88.0%, sensitivity of 81.3%, specificity of 85.7%, positive predictive value of 76.5%, and negative predictive value of 88.9%.

Table 2. AI-Supported Screening Classification Compared With Spirometry Diagnosis

AI Screening Outcome	Spirometry Positive, n	Spirometry Negative, n	Total, n (%)
AI positive	130	40	170 (34.0%)
AI negative	30	240	270 (54.0%)
Possible AI disease category*	—	—	50 (10.0%)
No significant findings	—	—	290 (58.0%)
Total spirometry-confirmed disease	160	340	500 (100.0%)

*The possible-disease category was incorporated into binary diagnostic comparison according to the prespecified threshold-based classification.

Table 3. Diagnostic Accuracy of AI-Supported Screening Against Spirometry

Diagnostic Indicator	Value
True positives	130 (26.0%)
True negatives	240 (48.0%)
False positives	40 (8.0%)
False negatives	30 (6.0%)
Overall accuracy	88.0%
Sensitivity	81.3%
Specificity	85.7%
Positive predictive value	76.5%
Negative predictive value	88.9%

ROC analysis showed excellent discriminative performance, with an AUC of 0.91. The optimal probability threshold was 0.48, indicating that participants with AI-predicted probabilities at or above this level were most appropriately classified as screening positive. Agreement between AI-based classification and spirometry was substantial, with Cohen's kappa of 0.78. Model calibration was acceptable, as indicated by a Hosmer–Lemeshow p-value of 0.41.

Table 4. ROC, Agreement, and Calibration Analysis

Analysis	Value	Interpretation
Area under ROC curve	0.91	Excellent discrimination
Optimal probability threshold	0.48	Best sensitivity-specificity balance
Cohen's kappa coefficient	0.78	Substantial agreement
Hosmer–Lemeshow p-value	0.41	Acceptable calibration

Overall, the AI-supported tool demonstrated strong concordance with spirometry and showed particular clinical value as a rule-out screening method, reflected by its high negative predictive value of 88.9%. The finding that spirometry confirmed chronic respiratory disease in 32.0% of smokers highlights a substantial burden of previously undiagnosed respiratory impairment in this public clinic population. These results support the potential utility of AI-assisted screening for prioritizing smokers who require confirmatory spirometry and further respiratory evaluation.

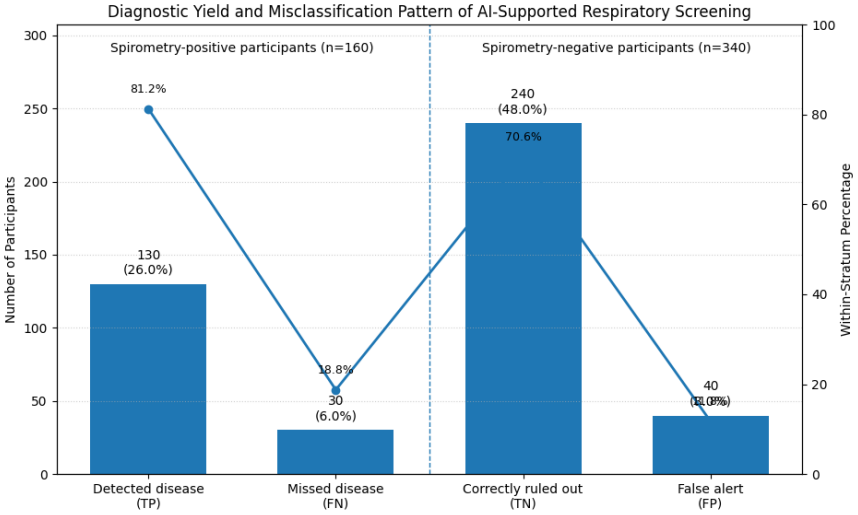

Figure 1 Diagnostic Yield and Misclassification Pattern

The AI-supported screening tool correctly detected 130 of 160 spirometry-confirmed cases, corresponding to 81.2% disease detection, while 30 cases were missed, representing 18.8% of diseased participants. Among 340 spirometry-negative participants, 240 were correctly ruled out (70.6%), whereas 40 were false alerts (11.8%). This pattern supports the clinical usefulness of the model as a screening tool, particularly because the proportion of missed disease remained lower than the proportion correctly identified among confirmed respiratory cases.

DISCUSSION

The present study demonstrated that an AI-supported screening tool achieved strong diagnostic performance for identifying undiagnosed chronic respiratory disease among adult smokers attending urban public clinics in Lahore. Compared with post-bronchodilator spirometry, the tool showed an overall accuracy of 88.0%, sensitivity of 81.3%, specificity of 85.7%, positive predictive value of 76.5%, and negative predictive value of 88.9%, with an AUC of 0.91 and substantial agreement with spirometry based on Cohen's kappa of 0.78. These findings suggest that AI-assisted screening may be clinically useful as a triage approach in high-risk smokers, particularly in public-sector settings where universal spirometry for all symptomatic or at-risk individuals is often difficult to implement. The high negative predictive value is especially relevant for screening because it indicates that the tool may help identify individuals who are less likely to have significant spirometric abnormality, while prioritizing higher-risk smokers for confirmatory pulmonary function testing.

The diagnostic yield observed in this study is consistent with emerging evidence that machine-learning models can support respiratory risk prediction by integrating clinical symptoms, smoking exposure, physiological parameters, and digital health inputs. Prior studies have reported that explainable AI frameworks can predict COPD risk in smokers using clinically accessible variables, while other machine-learning approaches have supported respiratory diagnosis, exacerbation prediction, imaging-based classification, and biomarker discovery in COPD and asthma-related conditions (16-20). The AUC of 0.91 in the present study falls within the upper range of previously reported AI performance in respiratory medicine and supports the potential applicability of such tools in real-world clinical screening. However, unlike many prior models developed in imaging-rich or tertiary-care environments, this study evaluated a screening approach based on public-clinic workflow variables, which strengthens its relevance for resource-limited healthcare contexts.

A clinically important finding was that spirometry confirmed chronic respiratory disease in 160 of 500 smokers, indicating that nearly one-third of this high-risk population had previously undiagnosed respiratory impairment. This reinforces the concern that smokers attending routine public clinics may

carry a substantial hidden burden of chronic airway disease. The AI tool correctly detected 130 of these cases, while 30 cases were missed. Although the false-negative proportion requires caution, the model's sensitivity suggests meaningful utility as an initial screening layer rather than as a replacement for spirometry. Similarly, 40 false-positive classifications occurred among spirometry-negative participants. In a public health screening context, such false alerts may be acceptable if they lead to further assessment, smoking cessation counseling, and closer clinical review, but excessive false positives could increase workload and unnecessary referrals if not managed through a clear diagnostic pathway.

The findings have practical implications for respiratory healthcare delivery in Pakistan and similar low- and middle-income settings. Public clinics frequently face constraints related to spirometry availability, trained respiratory personnel, equipment maintenance, and time-intensive diagnostic workflows. An AI-supported screening tool embedded into routine outpatient assessment could help standardize early risk identification, reduce reliance on subjective clinical judgment alone, and prioritize patients most likely to benefit from confirmatory testing. This approach may also support smoking cessation interventions by providing patients with individualized risk feedback. Nevertheless, implementation should not be interpreted as simple technological substitution; effective deployment would require training of clinic staff, validation in multiple healthcare settings, clear referral protocols, data privacy safeguards, cost-effectiveness evaluation, and ongoing monitoring for algorithmic bias.

The study has several strengths. It used a real-world public clinic sample, focused on a high-risk but under-screened population, and compared AI output against post-bronchodilator spirometry as the reference standard. The inclusion of agreement analysis, ROC assessment, calibration testing, and internal cross-validation strengthened the methodological evaluation. The use of routinely collectable clinical variables also increases the potential feasibility of the tool in settings where advanced imaging or specialist testing may not be immediately accessible. These features make the findings clinically relevant for primary-care screening pathways.

Several limitations must be acknowledged. The cross-sectional design prevents assessment of whether AI-supported screening improves long-term outcomes such as earlier treatment initiation, reduced exacerbations, slower lung-function decline, or improved quality of life. The study was conducted in urban public clinics in Lahore, so external validity to rural settings, private clinics, other provinces, and different ethnic or occupational populations remains uncertain. Although spirometry was used as the reference standard for airflow obstruction, chronic respiratory diseases such as bronchiectasis, interstitial lung disease, and mixed airway disorders may require additional imaging or specialist evaluation for definitive classification. The AI model was internally validated but not externally tested in an independent dataset, which limits conclusions about generalizability. Finally, cost-effectiveness, patient acceptability, health-worker usability, infrastructure requirements, and ethical governance were not formally evaluated.

Future research should prioritize prospective multicenter validation across urban and rural settings, with independent external datasets and predefined implementation outcomes. Longitudinal studies are needed to determine whether AI-supported screening leads to earlier diagnosis, better clinical management, improved smoking cessation uptake, and measurable reductions in respiratory morbidity. Further refinement of AI models could incorporate environmental exposure, occupational risk, longitudinal symptom patterns, wearable data, FeNO, imaging, or biomarker inputs, provided such additions remain feasible and cost-effective. Equity-focused analyses are also needed to ensure that model performance remains stable across sex, age, socioeconomic status, literacy level, and smoking-intensity subgroups.

CONCLUSION

AI-supported screening demonstrated high diagnostic accuracy, excellent discriminative performance, and substantial agreement with spirometry for detecting undiagnosed chronic respiratory disease

among smokers attending urban public clinics in Lahore. The tool identified a considerable hidden burden of respiratory disease and showed potential value as a practical triage method for prioritizing high-risk smokers for confirmatory pulmonary function testing. Although the findings support the promise of AI-assisted respiratory screening in resource-limited healthcare settings, broader implementation should be preceded by external validation, workflow integration studies, cost-effectiveness assessment, and evaluation of patient and provider acceptability.

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