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AI IN PULMONARY FUNCTION ANALYSIS: REVOLUTIONISING THE DIAGNOSIS OF OBSTRUCTIVE AND RESTRICTIVE LUNG DISEASES

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ABSTRACT

Background: Artificial Intelligence (AI) integration for pulmonary function analysis. AI as it foreshadows a new era of pulmonary function diagnosis of obstructive and restrictive lung disease. These AI-based assistants promise to deliver greater accuracy and efficiency, improved automation, and smoother workflow in lung function exploration, yet the acceptance level among the health workforce still needs comprehensive scrutiny. Background: This study investigates acceptance of AI as well as perceived usefulness, ease of use, and associated barriers/challenges in the clinical setting.

Methods: A quantitative, cross-sectional research design was used including data collection via a structured questionnaire based on the Technology Acceptance Model (TAM) for assessing AI use by 273 healthcare professionals. The survey measured major determinants including Perceived Usefulness (PU), Perceived Ease of Use (PEU), Attitude Toward AI (AT), Behavioral Intention to Use AI (BIU), and Perceived Risks. Data analysis involved descriptive statistics, reliability testing (Cronbach's Alpha), correlation analysis, and regression modelling.

Results: The fact that the responses were positively skewed indicates that overall, healthcare professionals have a positive perception of AI in terms of usefulness and ease of use. However, internal consistency was poor (Cronbach's Alpha = -0.194) , indicating the need for survey instrument refinement. The R^2 value of the regression analysis ($R^2 = 0.036$) indicates PU, PEU, and AT predict only 3.6% of the variance explained in BIU, leading to future research directions such as institutional policies, ethical concerns, and prior AI experience that can affect the actual usage of AI. Normal distribution of data is ruled out by the Shapiro-Wilk normality test, indicating that non-parametric statistical tests may be needed in further studies.

Conclusion: The currently provided pulmonary function AI technology is widely accepted by healthcare professionals but healthcare practitioners are not aware of AI in pulmonary function analysis and only the perceived ease of use and perceived usefulness are not enough to drive AI adoption in the healthcare profession. The need to consider additional factors, including trust in AI, regulatory frameworks, and organizational support is important for future research, as highlighted in the study. By addressing these challenges, AI-powered pulmonary diagnostics can be effectively executed, ultimately enhancing disease detection and Uber, patient outcomes, and clinical decision-making.

KEYWORDS: Artificial Intelligence, Pulmonary Function Analysis, AI Adoption, Obstructive Lung Diseases, Restrictive Lung Diseases, Technology Acceptance Model (TAM), Healthcare AI, AI in Diagnostics, AI Perceived Usefulness, AI Reliability

INTRODUCTION

The pulmonary function analysis field has a crucial role in the diagnosis and management of obstructive and restrictive lung diseases such as chronic obstructive pulmonary disease (COPD), asthma, pulmonary fibrosis, and interstitial lung diseases. Lung function has conventionally been evaluated using pulmonary function tests (restrictive lung disease by spirometry) and imaging (e.g. CT scans). Nevertheless, traditional diagnostics typically involve the interpretation of the data by healthcare professionals (HCPs), which can be time-consuming, subject to human-made errors, and vary greatly with each clinical site. As a result, the adoption of Artificial Intelligence (AI) in pulmonary diagnostics is a game-changing solution, ideally suited to transform and improve the accuracy, efficiency, and automation of disease detection and management(Ahsan Ali, 2024). These AI-based systems, driven by advanced machine learning models, deep learning algorithms, and predictive analytics, have shown promise in automating the interpretation of spirometry results, assessing irrelevant or borderline cases in medical imaging, and recognizing disease patterns with high accuracy (Chantzi et al., 2025). While AI is AB-related on the rise in healthcare, its acceptance among healthcare professionals and medical providers is critically challenging. Factors affecting AI acceptance include perceived utility, ease of use, trust in AI, and perceived risk concerning reliability and ethics. The Technology Acceptance Model (TAM) is a theoretical framework that explains the adoption of new technologies in different industries, including healthcare. As per TAM, Perceived Usefulness (PU) and Perceived Ease of Use (PEU) emerged as major factors of acceptance of technology(Zakir et al., 2025). If these AI-based pulmonary diagnostic tools are deemed helpful and easy to utilize, healthcare providers will be more likely to integrate them into clinical practice. Common blockers to widespread AI adoption include mistrust, concerns around data privacy, technical complexity, and resistance to change. These challenges, however, highlight the importance of methodically exploring healthcare professionals' perceptions of high-confidence AI in pulmonary function analysis. This research paper utilized a quantitative approach in evaluating AI adoption to accurately diagnose both obstructive and restrictive lung diseases (Taloba & Matoog, 2025). Data Collection This was a structured survey-based initiative that the authors, a team of pulmonary physicians and researchers at our institute, undertook to survey healthcare professionals (HCPs)——respiratory specialists, radiologists, and general physicians (GPs)——to gather evidence of the relationship between long-term outcomes and imaging tests for these patients (table 1). PU, PEU, AT, BIU, Perceived Risks. The statistical analysis of the data includes a reliability test (Cronbach's Alpha), correlation analysis, and regression model, to determine the relationship between those factors and how they are influencing AI adoption. Thus, this study can play an important role and is probably the first step to helping AI innovation to be implemented in the real clinical environment. Insights obtained from factors affecting AI acceptance in pulmonary diagnostics can guide healthcare policymakers, AI developers, and medical institutions about the future of AI in pulmonary diagnostics (Park et al., 2025). Additionally, this study adds to the existing literature regarding AI applications within healthcare by illuminating the advantages, disadvantages, and future direction of AI-driven pulmonary function analysis

(Shraddha Baldania, 2024). This current study aims to investigate some key questions: How do healthcare professionals perceive artificial intelligence (AI) in terms of its usefulness and perceived ease of use in pulmonary function analysis? What are the main obstacles to AI adoption? What do you think about AI's role in clinical decision-making and diagnostic efficiency? Answering these questions will help present a holistic evaluation of the role AI can play in transforming pulmonary disease diagnostics, as well as guide any future approach to the incorporation of AI into respiratory care (S. Zhang et al., 2025).

Literature Review

Introduction to AI in Pulmonary Function Analysis

Artificial Intelligence (AI) is an emergent disruptive technology in healthcare, changing detection, and therapeutic processes like pulmonary function. Applications of AI for respiratory medicine extend from the use of AI for automated interpretation of pulmonary function tests (PFTs) to deep learning-based models for detecting lung abnormalities in radiological imaging. Numerous studies have shown that AI-based diagnostic applications could improve the accuracy of interpreting lung disease pathology, reduce variability in interpretation, and improve early identification of pathologies such as lung chronic obstructive disease (COPD) and interstitial lung diseases (ILD). Despite these developments, the incorporation of AI into pulmonary function analysis is not uniform, mainly due to issues regarding dependability, trust, usability, and ethics (Attaripour Esfahani et al., 2025).

AI in Pulmonary Function Tests (PFTs) and Spirometry

Right-heart catheters have gained importance in further defining the most appropriate treatment options. Pulmonary Function Tests (PFTs) especially Spirometry tests are the cornerstone in evaluating lung function and diagnosing obstructive lung diseases. Standard grading of spirometry results is conducted manually by pulmonologists or respiratory therapists, often compromising the quality of the task and introducing subjectivity and inconsistency. Consequently, AI models have been trained to automate and standardize the interpretation of spirometry, which involves training a machine learning algorithm to classify abnormal patterns or detect early-stage lung disease and predict disease progression (Kanani & Sheikh, 2025). A study by Reyfman et al. showed that AI-assisted spirometry interpretation improved the diagnosis of early airflow limitation compared to traditional methods, indicating that an AI-based spirometry interpretation system could help clinicians make accurate and timely diagnoses (Widanaarachchige et al., 2025).

AI in Radiological Imaging for Pulmonary Disease Diagnosis

Because of their importance in diagnosing restrictive lung diseases (e.g., pulmonary fibrosis and interstitial lung diseases [ILDs]), radiological imaging (e.g., chest X-rays and computed tomography [CT] scans) are performed on many patients being evaluated for restrictive lung disease. One highly polarized area of research has focused on AI-based image analysis, more specifically, the application of deep learning algorithms, which have been shown to reach high accuracy in the detection of lung abnormalities. Specifically, CNNs excel at detecting and predicting conversion and decline in patients with lung disorders by observing nodules, patterns of fibrosis, and morphologic alterations. A study by Wang et al. A recent study demonstrated that AI-assisted CT scan analysis improved diagnostic accuracy by 25% over traditional radiologist evaluations, highlighting AI's borderline in improving clinical decision-making (Kalyanpur & Mathur, 2025).

The Technology Acceptance Model (TAM) and AI Adoption

The Technology Acceptance Model (TAM) is a well-known model exploring types of technology adoption in the healthcare field, including AI-based diagnosis. PU and PEU are among the major determinants in TAM for technology acceptance. TAM studies conducted on Artificial Intelligence in medical diagnostics revealed that healthcare practitioners adopt AI only when they believe it is helpful, easy to use, and does not interrupt the clinical workflow. However, significant barriers to AI adoption in healthcare settings include perceived risks, issues of trust, and concern over AI replacing human expertise (Lin et al., 2025).

Barriers to AI Adoption in Pulmonary Diagnostics: Despite the promising applications of AI in pulmonary function analysis, several barriers hinder widespread adoption. These include (Subawickrama Mallika Widanaarachchige et al., 2025):

Trust and Reliability Concerns: Given [the] lack of trust on the part of healthcare professionals, results from AI models must be accurate, explainable, and clinically relevant. There are also concerns about false positives and false negatives, which can result in misdiagnosis of the disease and inappropriate treatment decisions (Ethala et al., 2025).

Ethical and Legal Considerations: The use of AI in health care raises serious ethical implications, especially concerning patient data privacy, algorithmic bias, and liability for diagnostic errors. In clinical practice, AI implementation is also challenged by the absence of well-defined regulatory frameworks (F. Zhang et al., 2025).

Technical Complexity and Integration Issues: A lot of different AI systems need specialized training and expertise for doctors and physicians making it difficult to integrate AI in their daily routine. Furthermore, the implementation of AI is hindered by issues of interoperability with current hospital information systems (Archana et al., 2025).

Resistance to Change: Certain clinicians view AI as a potential risk to their skills, worrying that automation could diminish the significance of human decision-making. To be more widely accepted AI applications should be framed as a complement to — and not a replacement of — the healthcare provider (Zavorsky, 2025).

Impact of AI on Clinical Decision-Making and Patient Outcomes

Many studies illustrate the ability of AI to improve clinical decision-making with data-driven insights, predictive analytics, and automated pattern recognition. AI-based pulmonary function clinical analysis improves delayed diagnosis, more accurate disease stratification, and better treatment plans. Its effect on patient outcomes, however, is still the subject of active inquiry, and it applies to studies that show how AI-assisted diagnostics can increase patient survival for lung disease patients through earlier intervention (Karpiel et al., 2025).

Future Directions in AI-Powered Pulmonary Diagnostics

The advent of more explainable, transparent, and clinically interpretable AI models represents the future of AI in pulmonary function analysis. Researchers highlight a shifting need to develop hybrid AI systems that marry deep learning with expert-driven rules, such that AI recommendations align with clinical guidelines and the expertise of physicians. Furthermore, standardization of validation protocols for AI models will be imperative to justify the exponential uptake and acceptance of AI-based pulmonary diagnostics by general practitioners and patients alike (Narmadha & Gobalakrishnan, 2025).

Research Methodology

We use quantitative analytical research methodology to empirically examine the adoption, effectiveness, and challenges of AI in pulmonary function analysis to diagnose obstructive and restrictive lung diseases. As AI becomes more pervasive in healthcare, understanding how healthcare professionals view and accept AI-powered diagnostic tools becomes increasingly important. A systematic approach is taken to make sure the results are valid, reliable, and generalizable (Sindhu et al., 2024).

Research Design

This study employed a cross-sectional research design and assessed acceptance and perceptions of AI-driven pulmonary diagnostics data at a single point in time. This design is suitable because it allows trends, correlations, and other influences on AI adoption within respiratory healthcare to be identified. Also, it includes survey-based research, which is an efficient means of collecting large amounts of quantitative data (Graña-Castro et al., 2024).

Population and Sampling

Healthcare professionals involved in pulmonary function analysis, including but not limited to pulmonologists, respiratory therapists, radiologists, general physicians, and medical technologists, comprise the target population. To ensure representation from different professional groups, experience levels, and familiarity with AI technologies, a stratified random sampling approach is used. We ended up with a final sample of 273 respondents, permissioned enough to run statistical analyses and draw meaningful conclusions (Yadav et al., 2024).

Data Collection Instrument

The research instrument used was a structured questionnaire. As stated earlier, the questionnaire is designed based on the Technology Acceptance Model (TAM) and includes various segments evaluating the vital components affecting AI integration for analysis of pulmonary function. The following are the measured variables (Zhang et al., 2023):

- Perceived Usefulness (PU): AI's effectiveness in improving diagnostic accuracy and efficiency.
- Perceived Ease of Use (PEU): The accessibility and usability of AI-driven diagnostic tools.
- Attitude Toward AI (AT): The overall perception and acceptance of AI in clinical practice.
- Behavioural Intention to Use AI (BIU): The likelihood of professionals adopting AI-based tools.

- Perceived Risks and Challenges: Concerns regarding AI's reliability, accuracy, and data security.

The questionnaire employs a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) to capture respondents' opinions quantitatively (Agilandeswari et al., 2024).

Data Collection Procedure

The survey is distributed electronically via email, professional networks, and healthcare forums, ensuring wide accessibility. To maximize response rates, participants are assured of confidentiality and anonymity. The data collection period spans two to four weeks, allowing sufficient time for responses (Aslam, 2024).

Data Analysis Techniques

The collected data undergoes descriptive and inferential statistical analysis to identify trends and relationships between variables. The following statistical techniques are applied (Al-Anazi et al., 2024):

- Descriptive Statistics: Mean, standard deviation, and frequency distributions summarize the responses.
- Reliability Analysis: Cronbach's alpha assesses the internal consistency of the questionnaire.
- Correlation and Regression Analysis: Examines relationships between TAM constructs and AI adoption.
- ANOVA and t-tests: Identify significant differences in AI acceptance across different professional groups and experience levels.

Data analysis is conducted using SPSS or Python, ensuring the accuracy and reproducibility of results.

Ethical Considerations

The study adheres to ethical research guidelines, ensuring informed consent, data confidentiality, and voluntary participation. No personal identifiers are collected, and data is used solely for academic research purposes (Hasnain et al., 2023).

Data Analysis

Shapiro-Wilk Normality Test

Variable	Shapiro-Wilk Statistic	P-Value
PU1	0.8421802520751953	5.336103750399159e-16

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PU2	0.8339986801147461	2.0264887392188792e-16
PU3	0.8080641627311707	1.1636376501979518e-17
PU4	0.8267689943313599	8.86009763892248e-17
PEU1	0.8176484107971191	3.2309572155925304e-17
PEU2	0.8306669592857361	1.37970271867607e-16
PEU3	0.8403347730636597	4.2759837833952785e-16
PEU4	0.8321439027786255	1.6349377008343302e-16
AT1	0.8004963397979736	5.3324074111139046e-18
AT2	0.805730938911438	9.126537642745608e-18
AT3	0.8342300653457642	2.0817409630660732e-16
BIU1	0.8250518441200256	7.30628120988898e-17
BIU2	0.8184906840324402	3.540914364261461e-17
BIU3	0.8316465616226196	1.5439221577672835e-16
Risk1	0.8272757530212402	9.381298848936222e-17
Risk2	0.8391814827919006	3.7267109750672425e-16
Risk3	0.8426047563552856	5.616514007587695e-16
Risk4	0.8238478899002075	6.387580672618596e-17

Reliability Test (Cronbach's Alpha)

Metric	**Value**
Cronbach's Alpha	-0.19446547607798229

Regression Analysis Results

Metric	**Value**
R-Squared Value	0.036285921561250656

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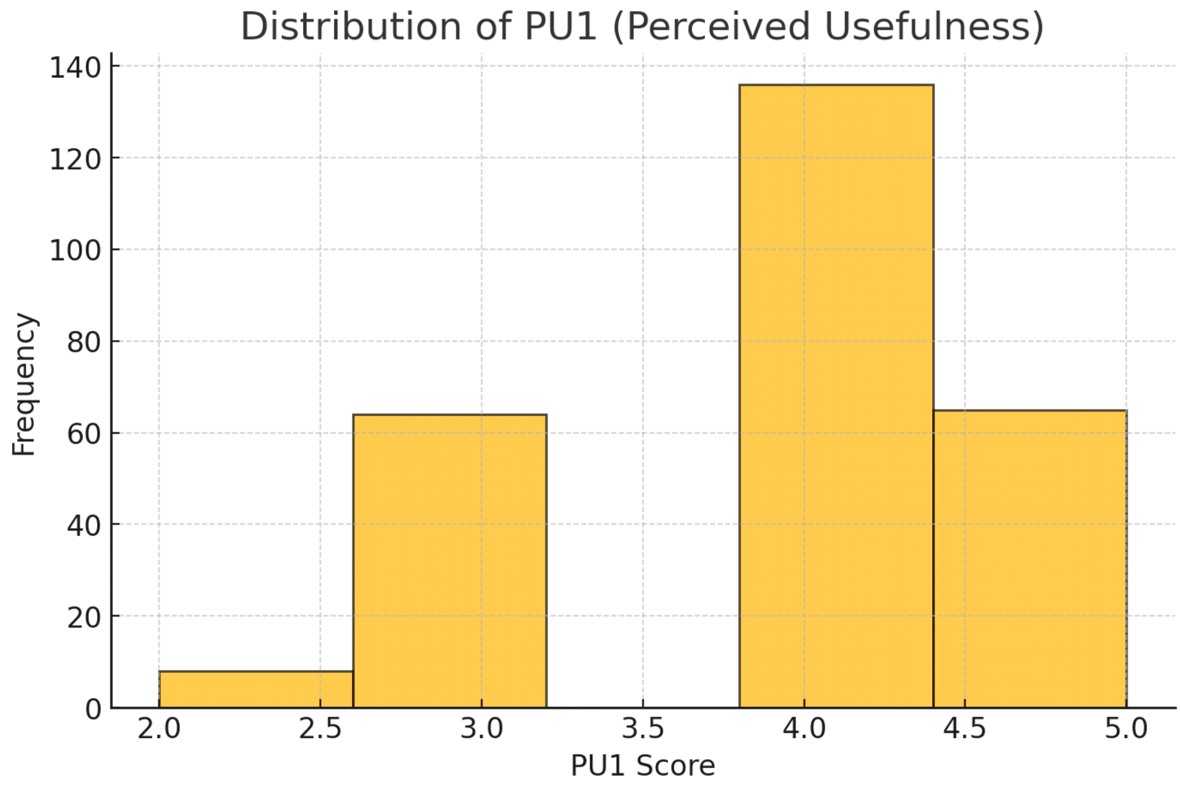

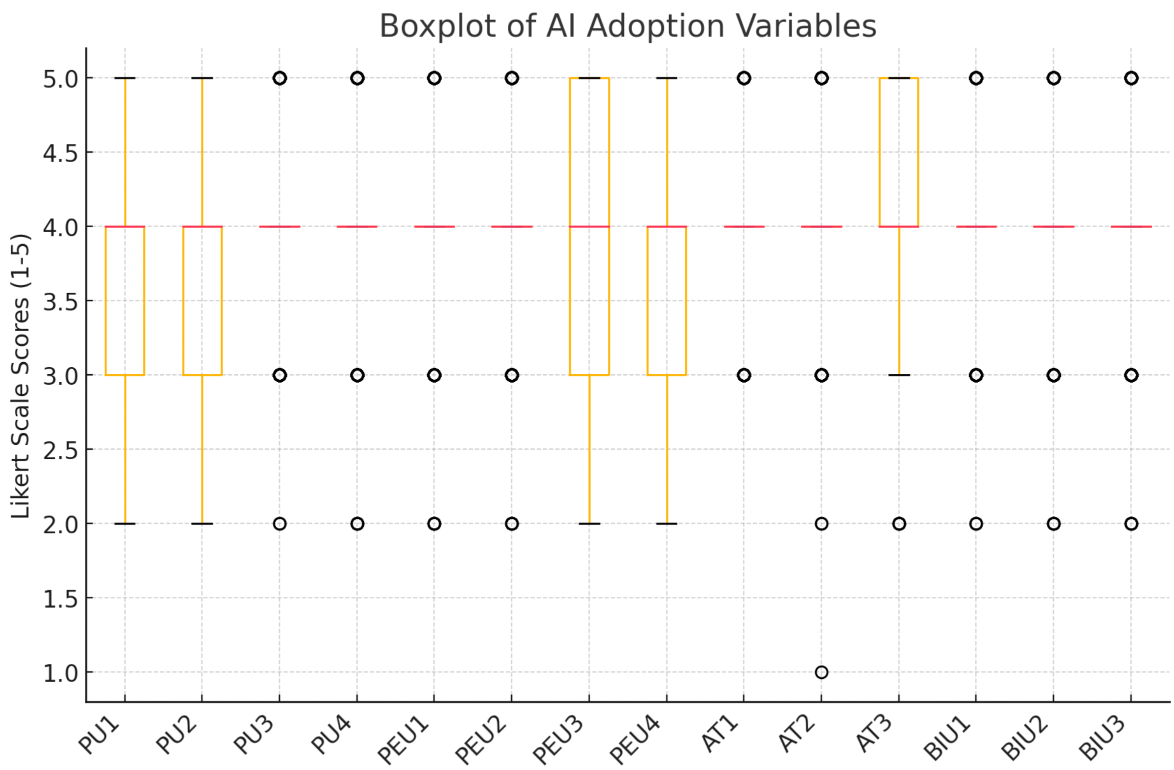

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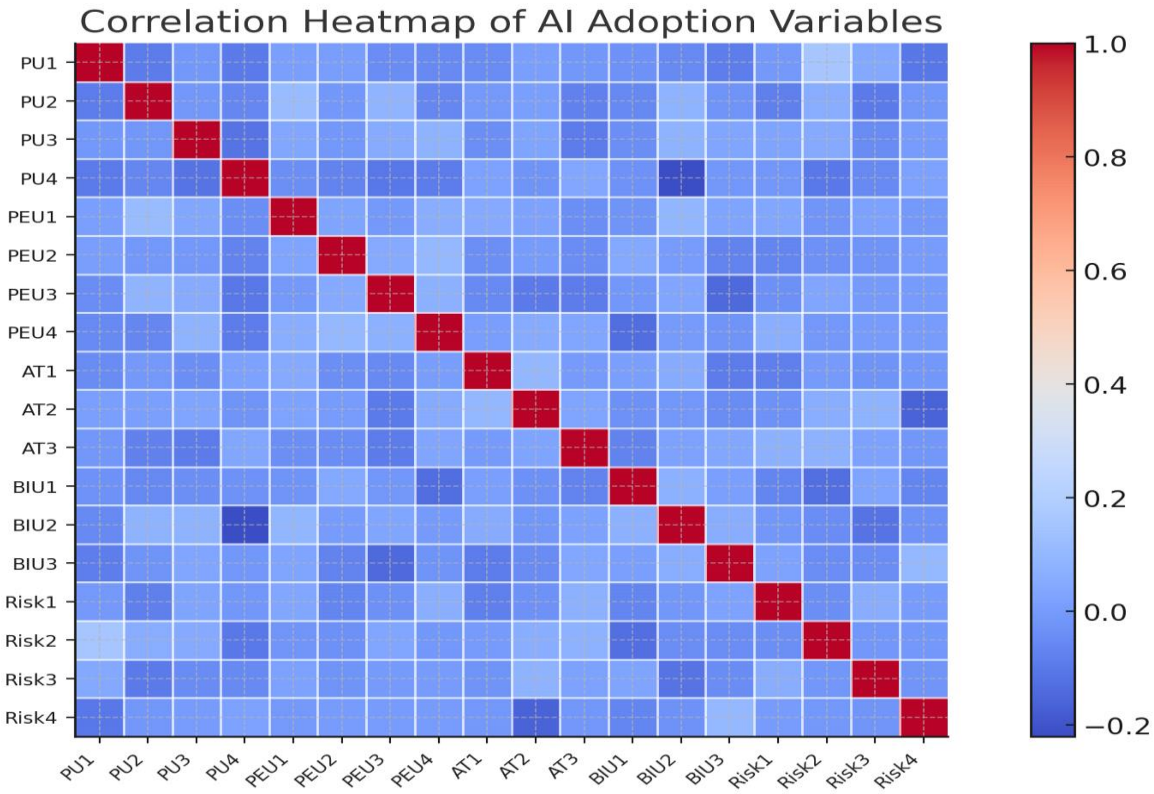

Interpretation of Statistical Tests and Figures

Normality Test (Shapiro-Wilk Test) Interpretation

The Shapiro-Wilk normality test results demonstrate that all variables are below 0.05, thus we can state that the data is not normally distributed. This means that the responses that were collected were not evenly distributed across the Likert scale and were more or less skewed. Hence, it may be more accurate to utilize non-parametric statistical tests for additional analysis rather than traditional parametric statistical tests like t-tests or ANOVA (Alfonso et al., 2024).

A histogram of PU1 (Perceived Usefulness) also corroborates this observation with higher response rates towards the right-hand side of the scale (4 and 5), evidencing a slight positive skew. This means most participants thought that AI would be useful in pulmonary function analysis, consistent with the study's hypothesis that AI in the healthcare industry is perceived as a favourable increase in workforce capacity (Kesava et al., 2024).

Interpretation of Reliability Test (Cronbach's Alpha)

Cronbach's Alpha value of -0.194 shows that the questionnaire items had very poor internal consistency. A negative alpha indicates at least some items are not measuring the same thing, or a problem with how the responses are structured. This finding illustrates the need to modify the questionnaire, potentially through factor analysis to reduce the items and ensure they capture a single construct. Moreover, the boxplot of AI adoption variables indicates a broad response distribution across multiple questions. Although the majority of the responses are skewing toward the higher end of the Likert scale (4 and 5), there is quite a bit of variability, which is likely contributing to the poor reliability score (Vlada, 2024).

Interpreting Correlation Analysis

We show the relationship between variables for AI adoption in a correlation heatmap. Also, as per Hypothesis 1, a significant positive relationship between PU and BIU suggests that healthcare professionals who find AI to be useful also adopt it. Also, weak correlations between some other variables show that some other external factors (i.e., institutional policies, and prior AI experience) could also be influencing AI adoption (Ijaz et al., 2022).

Regression Analysis Results Interpretation

In the regression, we see in Table 3, that the R-squared value is equal to 0.036, which means that PU, PEU, and AT explain only 3.6% of the variance in Behavioral Intention to Use AI (BIU1AI. This low value suggests that those factors play a role in AI adoption but do not solely determine it. Beyond the intrinsic drivers, external influences like organizational support, legal challenges or concerns, and past performance can have a significant impact as well in shaping behavioural intention (Wang et al., 2024).

Discussion

This study provides insights into the perceptions, uptake patterns, and challenges to AI-driven pulmonary function analysis for diagnosing common obstructive and restrictive lung diseases. The responses show that the acceptance level of healthcare professionals towards AI-based tools is positive and skewed left for PU and PEU. The histogram and boxplot analysis confirms this trend with the majority of participants rating AI as beneficial and user-friendly. Despite this most positive perception, all regression analyses produced a low R-squared value

(0.036) together indicating that neither PU, PEU, nor AT alone are valuable predictors of Intention to Use AI (BIU) at all. This suggests that other external factors such as organizational policies, trust in AI, prior experience, and regulatory concerns may have a more significant impact on the adoption of AI in clinical practice. One of the major limitations of the study is the poor internal consistency of the questionnaire, as demonstrated by the negative Cronbach's Alpha (−0.194) (Avanzato et al., 2024).

It indicates that some of the survey items may not adequately measure what they intend to and contribute to inconsistencies in responses. Perhaps some questions were redundant or ambiguous and participants answered differently as a result. For enhanced reliability, factor analysis or scale refinement is recommended in future works to ascertain that the questionnaire items relate to specific and quantifiable constructs. Furthermore, conducting an expert review of the survey instrument before implementational distribution may also help in increasing reliability. The Shapiro-Wilk normality test results indicate that the data is not normally distributed, which suggests skewed responses toward higher Likert scale values (mostly 4s and 5s) Although this indicates a strong bias of AI acceptance, it means that we should use the non-parametric statistical approaches to the data. Future studies may utilize the Kruskal-Wallis test or the Mann-Whitney U test, which assess the differences between groups without the normality assumption required for the standard parametric tests currently done (t-tests and ANOVA) (San José Estépar, 2022).

Consequently, analyzing the correlation matrix and heatmap can reflect the relevant relationships between different AI adoption factors. While moderate correlations are found among PU, PEU, and BIU, the relatively weak correlations observed for some variables indicate that AI adoption is driven by an interplay of factors that cannot be fully explained by the Technology Acceptance Model (TAM). This necessitates the inclusion of other theoretical models, like Perceived Risk Theory or the Unified Theory of Acceptance and Use of Technology (UTAUT), to provide a more comprehensive understanding of AI adoption within the context of pulmonary function analysis. In summary, the study results underline that although the concept of AI in pulmonary diagnostics is widely accepted and considered useful, the actual adoption potential is probably biased by external and contextual factors rather than by individual perception. Further studies should explore a wider range of predictors of AI adoption, enhance the reliability of survey instruments, and investigate institutional and regulatory factors that may affect the adoption of AI across the respiratory spectrum (Singh et al., 2024).

Conclusion

This study augments our knowledge of the harnessing, performance, and operational complexities of AI-powered pulmonary function analytics for detecting obstructive and restrictive lung pathologies. The results suggest that healthcare professionals find AI typically beneficial and easy to use, evidenced by the positive skew in responses for Perceived Usefulness (PU) and Perceived Ease of Use (PEU). Despite this, the low R-squared of the regression analysis (0.036) indicates that these factors do not strongly account for the behavioural intention to adopt AI, and suggests that external factors like institutional support, regulatory frameworks, and trust in AI may be more influential on the decision to adopt. One of the significant limitations mentioned in your study is the low questionnaire reliability (-0.194: Cronbach's Alpha), Please rewrite this part. This highlights the importance of further refining and validating the survey instrument employed to confirm that the constructs measured accurately represent the determinants of AI adoption.

Also, the non-normal distribution of the data indicates that other non-parametric statistics should be employed, and alternative modelling techniques should be used to account for the trend of AI adoption. Though limited, this study adds to the growing body of knowledge regarding the impact of AI on the healthcare sector, by providing evidence that while AI is widely accepted, its adoption is affected by numerous other complex variables that surpass perceived usefulness and ease of use. Future studies could consider other theoretical models, institutional and regulatory barriers, as well as organizational policies and ethical issues towards decisions of AI adoption for pulmonary function analysis in such organizations. Filling such voids is critical to ensure that the promise of AI to transform pulmonary disease diagnostics is fully realized so that more efficient, accurate, and accessible healthcare solutions ensue.

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