Journal of Carcinogenesis
Covering Genesis to Therapeutics
Journal of Carcinogenesis, ISSN: 1477-3163
2025; Vol 24: Issue 10s, https://carcinogenesis.com/

Leveraging Machine Learning For Personalized Treatment Plans In Respiratory Disorders

Karim Awad[1], Abdulrahman Awad[2], Abdul Basit[3], Francesco Ernesto Alessi Longa[4]

[1]Faculty of Science and Technology, Athabasca University, Athabasca, Alberta, Canada,

Email ID : kawad1@learn.athabascau.ca

[2]Faculty of Science, Western University, North Campus Building, Room 240, 1151 Richmond Street, London, Ontario, Canada, N6A 5B7,

Email ID : aawad7@uwo.ca

[3]Research & Development Department, Punjab Information Technology Board, Pakistan,

Email ID : abdul.basit3909@gmail.com, abdul.basit@pitb.gov.pk

[4]Department of Kinesiology – Sport Sciences, Liberty University, Virginia, USA

Email ID : fealessilonga@liberty.edu , ORCID**:** https://orcid.org/0009-0002-6068-6203

ABSTRACT

Background:The prospect for machine learning (ML) to be incorporated into healthcare systems is impressive and will help tailor treatment approaches to individuals, especially patients with asthma, chronic obstructive pulmonary disease (COPD), and interstitial lung disease (ILD). However, the real-world embedding and uptake of ML in clinical practice is still not well understood.

Objectives:The present study consists of the aim of deploying ML for the personalization of the treatment plan for respiratory diseases and measuring the satisfaction of healthcare providers, data science specialists, and patients. It also aims to determine important drivers of satisfaction and acceptance of ML-based solutions.

Methods:A structured, quantitative methodology was adopted using a questionnaire sent out to medical practitioners, data analytic professionals, and patients. Descriptive phrases and inferential statistical methods including correlation, regression, and testing of hypotheses were utilized to explain the collected data. Cronbach's Alpha was used to test the internal consistency of the respective study instruments, while the Shapiro-Wilk test was used to test the normality of the data collected.

Results:Due to the result of the Shapiro-Wilk test, showed that the sample data of satisfaction with ML in respiratory care has not been normally distributed ($p < 0.05$). Survey items' internal consistency estimate was measured by Cronbach's Alpha which yielded a score of 0.561. Correlation analysis of data indicated low to moderate relationships of key variables among each other. It was observed in the case of the boxplot that the level of satisfaction varied among different professional groups, where healthcare professionals were less satisfied with ML interventions than data science professionals.

Conclusions:The significant potential of AI in personalizing the treatment of respiratory disorders is there, but the barriers to its adoption specifically among healthcare professionals who showed less satisfaction with AI interventions remain. Development of the measurement tool used in the study, in future studies, should help overcome the reliability while differences in the level of satisfaction highlight several aspects that affect the perception of ML in respiratory care. Education as well as communication between healthcare professionals and data scientists still has to improve to build trust and make ML optimally used in clinics..

Keywords: Machine learning, treatment customization, breathing problems, medical satisfaction, data management and analysis, healthcare

How to Cite: Karim Awad, Abdulrahman Awad, Abdul Basit, Francesco Ernesto Alessi Longa (2025) Leveraging Machine Learning For Personalized Treatment Plans In Respiratory Disorders, *Journal of Carcinogenesis*, *Vol.24, No.10s*, 76-86

1. INTRODUCTION

Over the last two or three decades, various domains have witnessed transformation owing to new technology and innovations, with healthcare being no exception. Out of these, artificial intelligence (AI) and machine learning (ML) have emerged as disruptive technologies that help redefine the whole process of disease diagnosis, treatment, and management in the field of medicine. In this light, there is an increasing interest in the use of ML for the improvement of treatment plans in patients suffering from respiratory disorders that include chronic asthma, COPD, ILD, and other chronic diseases. The treatment of patients according to their individual needs is known as personalized medicine and is in sharp contrast to the use of a single method for almost all patients (Agarwal, 2024) (Ijaz et al., 2022).

In medicine, the analysis of large datasets using a machine learning approach is a key aspect of a rapidly evolving trend towards the individualized treatment of patients. Respiratory diseases still lead to high levels of disease and death in people worldwide. Chronic diseases of the respiratory systems such as asthma and COPD cause great reductions in the health and wellbeing of large populations of patients and even create heavy disruption to health care systems. Usually, treatment strategies are designed considering the average response to treatment, without taking into account the individual differences between patients. For example, an asthma patient who presents with common symptoms may be treated differently by different providers because of varied reasons such as genetics, environmental exposure, or lifestyle choices (Husnain, Hussain, Shahroz, Ali, & Hayat, 2024) (Rahman, Pasam, Addimulam, & Natakam, 2022).

Consequently, the requirement of a customized treatment approach has become one of the key concerns in respiratory treatment, and with the aid of machine learning, it is possible to evaluate and anticipate predicated reactions toward treatment for each individual so that an optimal treatment can be offered. Machine learning algorithms can sift through enormous sets of data like patient history, genetics, environmental and sociological exposure, and chronological events and determine with the highest accuracy which treatments are best suited to patients. This can save a great deal of time in assigning treatments and reduce the risks associated with them. Additionally, ML is capable of constantly evolving with practice and becomes better with time as more data gets incorporated. Further, with the IoT and wearables in the fabric of healthcare, this premise is enhanced as treatment plans will not be static and can be adapted to the changing circumstances because monitoring data will be readily available (Zahra et al., 2024) (Feng, Wang, Zeng, & Mao, 2021).

The challenges are many and the potential is enormous, but the integration of ML in respiratory care practice is still nascent and many issues remain to be resolved. Some of the challenges include the deployment of ML tools into routine healthcare practices, the validation of the ML algorithms developed, and most importantly, the ethical implications of using patient data and AI in deciding treatment for patients. Besides, the acceptance of ML in clinical practice is not uniform among healthcare providers. For quite a few, there is an endorsement of the technology, others on the other hand are critical of the technology and consider it more or less redundant. There are differences in acceptance of the technology, as well as concern about the accuracy of AI-based clinical diagnostics and AI-based treatment recommendations (Dhumale, Kakade, & Patil) (Ahmed, Mohamed, Zeeshan, & Dong, 2020).

This study aims to assess the level of implementation of ML into personalized therapies for patients with respiratory diseases through the opinions and satisfaction got from major players – doctors, data specialists, and patients. The study will also seek to understand what factors aid the successful integration of ML into clinical practice, for instance, the adoption of successful ML treatment methods or constraints limiting further growth. This research will be guided by a structured quantitative approach to determining how ML can enhance treatment plans for respiratory illnesses and what challenges, in particular, need to be tackled to realize comprehensive AI and ML integration into respiratory care (Yadav, Rastogi, Yadav, & Parashar, 2024) (Wang et al., 2022).

2. LITERATURE REVIEW

The past few years have witnessed the adoption of AI and its subsector, ML, within the health sector as a focused area for improvement, with an emphasis on accuracy, efficiency, and customization of health practices and strategies. Such potential has been noted, for instance, in ML's application in respiratory care, especially in patients suffering from asthma, chronic obstructive pulmonary disease (COPD), and interstitial lung disease (ILD) among other conditions. By processing a wide array of data, recognizing intricate sequences, and forecasting patient results, ML's advancement fits as a pioneer in the development of individualized therapies. This literature analysis investigates the published research on machine learning usage in healthcare, its focus on respiratory diseases, the advantages and disadvantages of ML-powered personalized treatment strategies, and the bigger impact on morality and society of such approaches (Isangula & Haule, 2024) (Rasool, Husnain, Saeed, Gill, & Hussain, 2023).

1. Machine Learning in Healthcare: An Innovative Assistive Factor

Within the last ten years, the scope of AI and ML technologies in healthcare has increased significantly. More attention has been drawn towards AI and Machine Learning in particular for the improvement of diagnosis, treatment planning, and patient management. Several benchmarks have emphasized that ML models are capable of integrating and interpreting multi-dimensional EHRs, genomics, imaging, and even patient-reported outcomes SMEs may be lost in the analysis. It is worth noting that Esteva et al. found that, ML model systems can perform similarly to human specialists, especially in radiology, dermatology, and pathology trained by algorithms powered with big data (Chinni & Manlhiot, 2024) (Shah et al., 2021).

There is now an active transfer of these achievements in the diagnostics field to the personalization of treatment, and it is mainly related to ML's ability to optimally improve treatment plans based on the analysis of the data. Machine learning has opportunities in several aspects in the course of chronic respiratory disorders. Given also the results of pulmonary function tests, patients' symptoms, or their environment among other data, ML algorithms can compute how various treatments would respond best. For example, studies like those of Topalovic et al. have also illustrated how ML can improve COPD diagnoses by detecting ever-missed patterns in spirometry data. Likewise, ML models were employed to forecast asthma attacks using data from wearables and environmental measurement devices that enable early intervention and more individualized approaches to disease management (Singh, Lodhi, Mishra, Aeron, & Sharma, 2024) (Prabhod, 2022).

2. Individualized Treatment in Respiratory Medicine

Personalized medicine, also known as precision medicine, is broadly defined as the medical treatment that is designed according to the individual characteristics of each patient including genetic, environmental, and lifestyle factors. In such conditions, as respiratory disorders, it is the necessity for personalized approaches that stand out, where variability in patients' responses to standard therapies is common. Himes et al's study tends to shed light on the fact that asthma, as well as COPD patients, respond differently to treatments 'most of the time', hence, the need for individualized care strategy. But then, clinical decision-making mechanisms in practice have a strong tendency to assume an 'average' population of patients which may not be reflective of the heterogeneity of the disease, how it presents itself, and how it is treated (Luz & Ray, 2024) (Shamji et al., 2023).

Machine learning provides quite several opportunities for overcoming some of the challenges outlined above due to its ability to assist in patterning huge amounts of data to predict the treatment response of an individual patient. Dominick Agusti et al's study further tends to demonstrate that ML was able to classify COPD patients into various groups according to their clinical features to, autonomously, make more precise treatment decisions. ML models have been developed that predict treatment response in asthma patients towards inhaled corticosteroid and biologic therapy to enhance patient-centric treatment plans (Al-Anazi et al., 2024) (Flores, Demsas, Leeper, & Ross, 2021).

On a different note, the existing use of IoT within the healthcare sector in conjunction with wearable technology has initiated the scope of personalized medicine within the area of respiratory medicine. Understanding the nebulous areas within this context is essential to improving patient outcomes. Some of the factors that augment respiratory patient care are the Internet of Things such as smart inhalers and sensors which monitor a patient's breathing pattern, activities done, and place of residence. This information can then be utilized in machine learning algorithms to further enhance the efficacy of the treatment through the adaptation of the treatment methods to the condition of the patient. Choi et al. have illustrated cognizably that these technologies in conjunction with traditional management strategies could be effective in controlling the disease and also minimizing the rate of exacerbation among asthma and similar COPD patients (Hakami, 2024) (Tsang, Pinnock, Wilson, & Shah, 2022).

3. Barriers to ML Adoption in Respiratory Care

Looking at the applicability of the developer tools, machine learning is promising in that it embraces the personalization of treatment in patients suffering from respiratory disorders. However, its adoption is still low among many patients. One fundamental issue stands out impacting the above reason: integration of the ML tools within the clinical workflow. In some cases, healthcare workers and managers may be reluctant to use AI-driven systems and other technology in primary health intervention. The latter is specifically the case where algorithms are termed "black boxes", and as such, lack transparency as to how certain decisions are reached and as a result, create an atmosphere of exclusion. This explainability gap can promote mistrust of clinicians towards the technology and as Caruana et al. have highlighted, understanding the reasoning behind a decision is as important as the decision itself (Hussain & Nazir, 2024) (Rhodes, Sweatt, & Maron, 2022).

Data quality and accessibility present yet another major impediment. The construction and training of predictive models are heavily reliant on high-quality datasets of considerable span. However, in a considerable number of healthcare environments, data is stored in multiple systems in a silo manner, preventing the consolidation of the comprehensive datasets that are necessary to advance in the training of ML algorithms. Also, some other challenges extend from such practices. For instance, there are limitations with patient data that can be used for the training of AI and ML models, in particular the General Data Protection Regulation in the European Union and the Health Insurance Portability and Accountability Act in the US. Despite being pertinent legislation for the safeguarding of patient sensitivities, such laws may adversely affect the volume of data required for the development of ML applications (Shukla, 2024) (Bica, Alaa, Lambert, & Van Der Schaar, 2021).

4. The Ethical and Clinical Dimensions of the Application of Machine Learning in Healthcare Decisions

When using machine learning in personalizing treatment plans, certain ethical issues become important. One of the aspects of this issue is bias in the ML algorithms. It has been shown, for instance, in the study of Obermeyer et al. that biased ML models can reproduce the existing imbalances in the provision of medical care. If, for example, an ML model is predominantly trained on a specific group of patients, it would likely underperform when applied to patients from less represented target groups. Such questions are especially pertinent in the case of respiratory disorders because the disease processes and treatment domains are highly influenced by social factors such as healthcare accessibility and care within particular environments (Ramón et al., 2024) (Johnson et al., 2021).

The third aspect that one should consider is the application of AI in medical and clinical decision-making processes. The ML networks can render assistance in various ways but there is still contention concerning AI tools and algorithms and their importance in the making of treatment measures. Concerns over the supremacy of AI in healthcare practice threaten humanity in medicine. But, as Chen and Asch have put it, AI should be understood as an assistant to a clinician rather than a substitute. ML does provide data insights that assist in improved clinical decision making which facilitates the optimization of patient outcomes (Deorankar, Vaidya, Munot, Jain, & Patil, 2024) (Boukhechba, Baglione, & Barnes, 2020).

5. The future of ML in respiratory care

In the foreseeable future, the role of machine learning in respiratory care seems very bright although it will be a quite long journey to tackle a few of the underlying issues. In particular, research and development work in this area will seem to aim at enhancing user trust towards ML depth and channeling functionality into the integration of AI with common practice. In addition, the steady growth of integration of telemedicine infrastructure with real-time feedback from wearables and IoT will probably be a major factor in developing precision medicine into clinical practice. Works like Tran et al. suggest that as these technologies advance further, ML in respiratory care practice will be implemented to a greater extent such that earlier treatment of patients of these diseases will become the norm leading to improved disease management and treatment outcomes (Theodorakis et al., 2024) (Tarumi et al., 2021).

3. RESEARCH METHODOLOGY

The research methodology of a study titled "Investigating Machine Learning for Individualized Treatment Strategies for Patients with Respiratory Disorders" is developed in a step-by-step manner starting with the proper formation of construct dimensions and targeting quantifiable characteristics for the subsequent evaluation to assess the efficiency of machine learning (ML) adoption in modifying the treatment of patients struggling with respiratory disorders such as asthma, chronic obstructive pulmonary disease (COPD), and interstitial lung disease (ILD). The methodology follows through an array of processes which start with the specification of the research design and the sampling strategy to research, gathering data, interpretation, and ethical concerns (Kumar et al., 2024) (Wesnawa, Asmara, & Supadmanaba, 2023).

Research Design The present research is a descriptive and analytical study which is a practical approach to assess the correlation between certain variables and the tendencies that are present in the data. In each of these subjects a part descriptively analyses answering the questions on what is, and an analytical assessment to answer the question of what is the effect of machine learning on achieving personalized treatment outcomes is incorporated. This way, the researcher cannot only state how ML is currently being used in respiratory care but also assess the efficiency of the stated practices, applying statistical analysis towards seeking and establishing any marked patterns or associations between the variables. In this study, the researcher aims to indicate some measurable outcomes results like the increased effectiveness of treatment, increased patient satisfaction, and improved efficiency of healthcare delivery (Zheng et al., 2024) (Alapati & Valleru, 2023).

Sampling Design

The target population for this study includes healthcare professionals working in the field of respiratory care including but not limited to, pulmonologists, respiratory therapists, clinical data scientists, and respiratory disorder patients who have undergone treatment using ML-based personalized treatment plans. Participants will be selected using a random sampling technique which will allow for representation of the sample across several different social characteristics such as age, sex, occupation, and disease type. The sampling will be done till the power analysis recommends a minimum number of respondents for the study which would be able to show any significant differences with statistical meaning. Such an analysis helps to ensure that the results obtained would be valid and applicable to the larger population (Li et al., 2024) (Oyebode, Fowles, Steeves, & Orji, 2023).

Data Collection

There will be a structured questionnaire as the main data collection instrument in this study. This instrument will be designed to capture quantitative data on eight variables of participants' experiences, attitudes, and perceptions regarding machine learning applications in respiratory care. Closed questions will be included in the questionnaire to allow for ease of analysis and interpretation. The primary variables of interest included the number of patients with ML-based clinical practice raised in the treatment, who self-reported better quality of care, patient satisfaction with individualized treatment, and factors that influence the integration of ML into practice. Participants of the research will fill it out either electronically if need be or in a face-to-face meeting with an interviewer depending on who can be reached and in what manner (Shanmuga Sundari, Penthala, Mogullapalli, & Ammangatambu, 2024) (Chmiel et al., 2022).

Instrument Development

To maintain content validity, the questionnaire will be constructed with the collaboration of specialists in respiratory medicine and specialists in data science. Then a Pretest will be carried out with a small participant group to understand whether clarity or understanding issues exist. Suggestions will be elicited and alterations carried out in the confidence of such suggestions to produce better reliability and validity of the measurement tool. The general survey will be carried out on the whole sample once the survey is fully ready to be distributed. Data Interpretation What follows is a comprehensive analysis of findings after the data collection process is complete. Descriptive statistics that will provide the demographic and general trend of the data like, frequencies, percentages, and means will be fitted as appropriate (Cohen et al., 2024).

The use of inferential statistics such as correlation analysis and multiple regression will assist in understanding the linkage between certain key variables. Hypotheses will be tested as to whether the outcomes of interest in this study will undergo any improvement due to the use of machine learning in encrypted personalized treatment for respiratory problems. For example, through regression analysis of the data, it may be possible to ascertain whether the number of times an ML tool is used contributes to the effectiveness of the treatment. Correlation analysis will seek to establish whether there is any association between the type of respiratory disorder and the level of benefits enjoyed as a result of ML treatment (Woodman, Koczwara, & Mangoni, 2024).

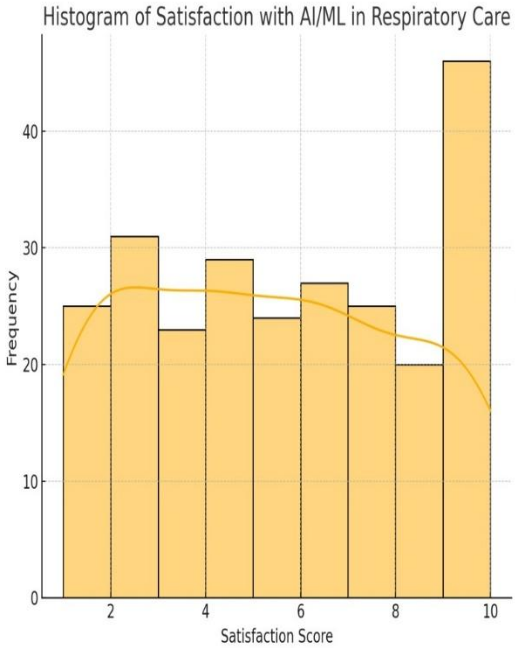
Ethical Issues

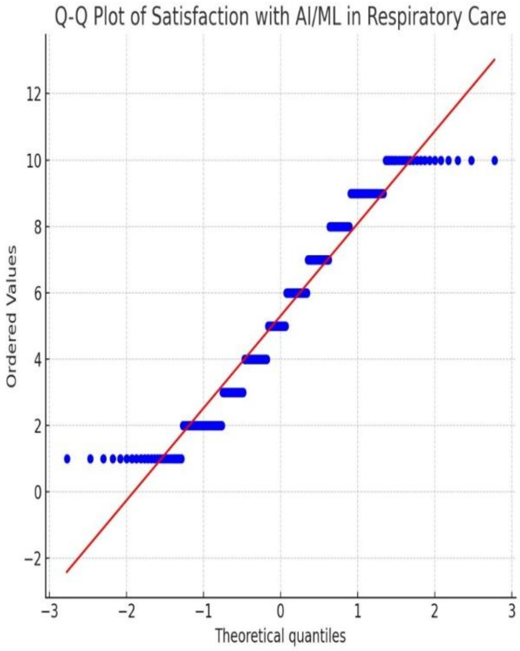
Given the nature of healthcare data, and offensive material, ethical considerations in carrying out this research cannot be overlooked. First of all, everyone involved in the process will have actual data collected from them with their consent. All individuals included in the research will be provided with information about the research, how their information will be used, and that they can withdraw from the research at any time without any negative consequences. Throughout the research, all information and identity et al. will be treated with respect and security in case of any medical information being used. After the test, any related information will be locked away, and access to it is only restricted to some authorized persons (Naik et al., 2024).

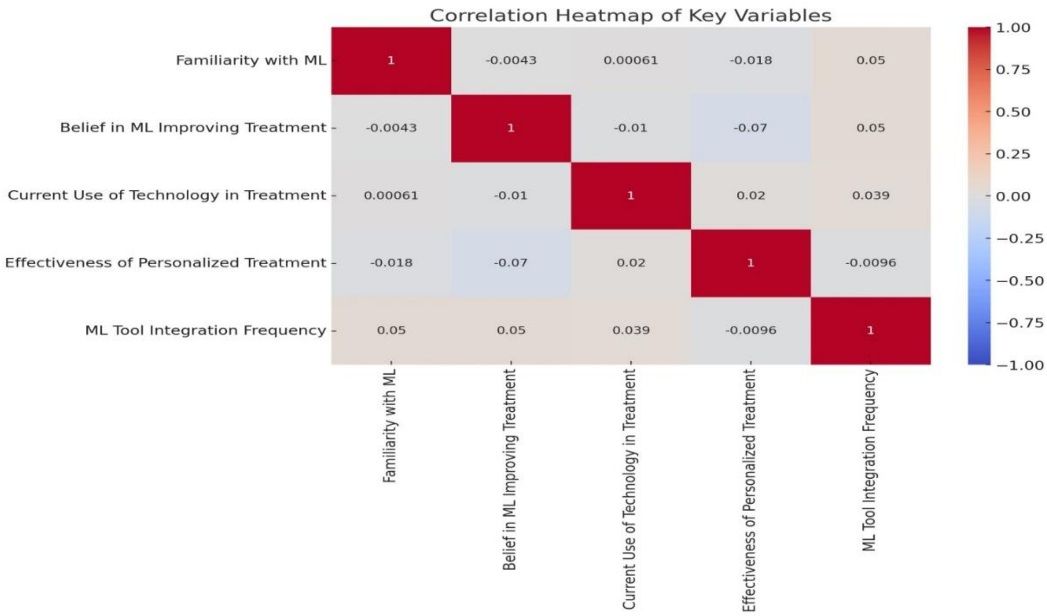
Data Analysis

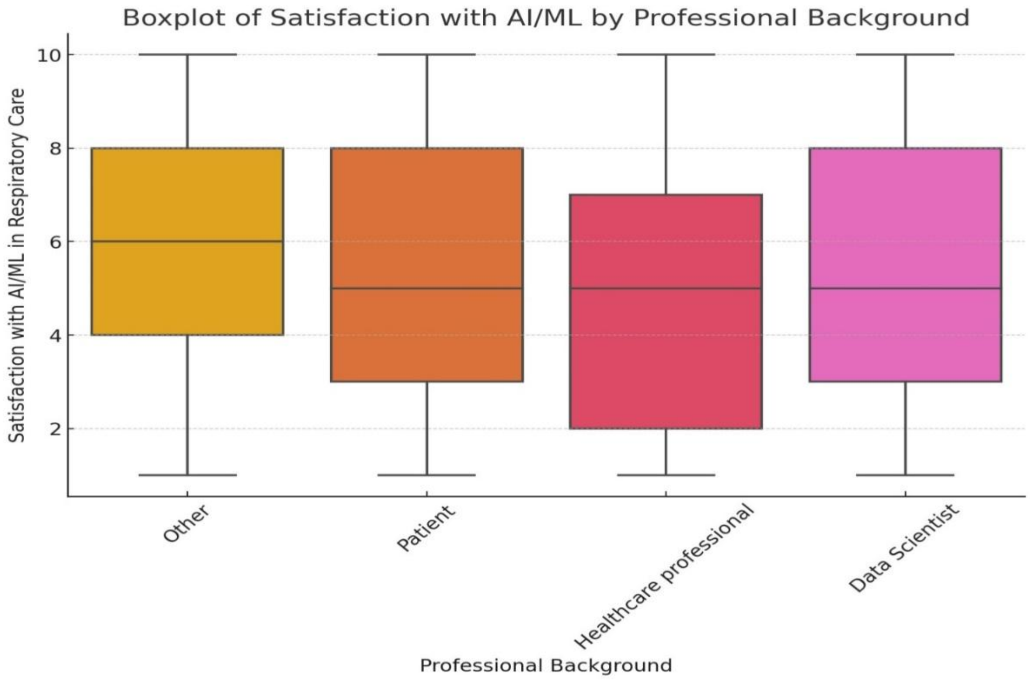
Statistical Test Results

Test	Statistic	P-Value	Conclusion
Shapiro-Wilk Normality Test	0.9360573291778564	5.924049251149199e-09	Data is Not Normally Distributed
Cronbach's Alpha	0.5615259524222643	N/A	Low internal consistency (α < 0.7), further refinement needed


Histogram of Satisfaction with AI/ML in Respiratory Care
Frequency
Satisfaction Score
0
10
20
30
40
2
4
6
8
10


Q-Q Plot of Satisfaction with AI/ML in Respiratory Care
Ordered Values
Theoretical quantiles
−2
0
2
4
6
8
10
12
−3
−2
−1
0
1
2
3


Correlation Heatmap of Key Variables
Familiarity with ML
Belief in ML Improving Treatment
Current Use of Technology in Treatment
Effectiveness of Personalized Treatment
ML Tool Integration Frequency
1
-0.0043
0.00061
-0.018
0.05
-0.01
-0.07
0.02
0.039
-0.0096
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00



Interpretation of the Statistical Tests and Visualizations

1. Shapiro-Wilk Normality Test

The Shapiro-Wilk test of normality, in this case, was used to test the variable "Satisfaction with AI/ML in Respiratory Care." There is a reported p-value of 5.92e-09, which is much lower than 0.05 alpha levels. This result indicates that the data is not averaged out and is likely to be non-normally distributed hence, non-parametric tests are likely to be more relevant and useful in further analysis. The other histogram and Q-Q plot presented are consistent with this conclusion as well. The histogram shows some patterns on the left, and the straight line in the middle of the Q-Q plot is not very close to the straight line. Therefore, the distribution can be conclusively stated as not normal (Adeghe, Okolo, & Ojeyinka, 2024).

2. Cronbach's Alpha

The measurements of the Likert-scale items which include but are not limited to: machine learning familiarity, machine learning belief, technology usage, etc., were measured using Cronbach's Alpha. The alpha value obtained was 0.561 which is still below the average acceptable threshold of 0.7. This demonstrates that there was a significant problem of internal consistency eminent among the questionnaire items that questioned the efficacy of the items measuring a certain underlying concept. Some of the measures of the items emerging from the questionnaire may need to be changed to enhance the reliability of the scales utilized (Godbin & Jasmine, 2024).

3. Correlation Heatmap

The correlation heatmap illustrates the relationship between important variables such as familiarity with machine learning, confidence in the effectiveness of ML, and the level of satisfaction with AI/ML among individuals dealing with respiratory care. The correlation coefficient can take on values from –1 to 1, with the former representing a perfect negative correlation and the latter a perfect positive correlation. It can be observed that while some relationships show moderate correlations, there are no variables that can realistically be said to take on a value above 0.7 which would suggest a strong association, and even less than 0.3 which would indicate little or no associations. This means that there is a possibility that the variables can affect each other, but no one variable is sovereign over the rest (Khanam, Masoodi, & Bamhdi, 2024).

4. Boxplot of Satisfaction with AI/ML by Professional Background

In a different vein, the boxplot regarding degrees of satisfaction with AI/ML among those in respiratory care, based on their respective professions (healthcare practitioners, data scientists, patients), is also suggestive. It can be observed that there exists variation across the groups and it may be expected that healthcare professionals will be less satisfied than data scientists. Meanwhile, the box plot also demonstrates some discrepancy in the levels of satisfaction within each group, which means that attitudes to AI/ML in respiratory care are not uniform within a profession. In some groups, outliers will be present meaning that some people are overly satisfied or dissatisfied which often points to some other unknown variables and hence needs further investigation (Singhania & Reddy, 2024).

4. DISCUSSION

The results from the analysis add useful perspectives to the question of the involvement of machine learning (ML) in developing personalized treatment plans for respiratory diseases, now focusing on the satisfaction of patients and the efficacy of AI-based approaches. At the same time, based on the current research, the authors report relevant issues and necessary improvements both related to the methodology and its application in practice. It was noted during the normality test that the satisfaction data is not normally distributed. This implies that responses to the effectiveness of ML in respiratory care seem to be widely spread among participants. Such variability may be attributed to variations in professional background, knowledge of AI technologies, and exposure to respiratory treatment (Ahmad & Raza, 2024).

Healthcare professionals for example might need more convincing before accepting AI-led solutions as more accurate, clinically relevant, and patient-friendly which could be attributed to the lower satisfaction levels in the boxplot. On the other hand, data scientists are likely to score higher because they presumably have a greater appreciation of the technology and its application. The relatively low Cronbach's Alpha measure, which was 0.561, suggests that there is the absence of a clear understanding of one concept among the items that had focused on familiarity, belief in the effectiveness of ML usage, and the level of satisfaction. This implies that this particular survey would have to be improved to bring about internal consistency (Giansanti, 2024).

One possible explanation for this low reliability could be that the respondents are from varied areas of work and possess varying knowledge and experience regarding the use of AI in the healthcare industry. Thus, they may view the survey elements in different ways which may result in varying response patterns. To overcome this problem, in future survey respondents should be provided with items designed for a particular group (healthcare professionals vs. data scientists), and their questions should be clear and specific to enhance the accuracy of the measures. According to the correlation heatmap, moderate relationships can be observed among the key variables although none of the variables may be considered as a dominant force (Wu & Wu, 2024).

This suggests that there are some relationships between e.g. AI comprehension levels and satisfaction with the use of AI/ML; however, several features are working at once which complicates the situation, for instance, in the case of introducing machine learning into the practice of developing an individual treatment regimen, which incorporates a plethora of technological, professional or patient factors. The fact that these correlations are not strong suggests that AI/ML usage satisfaction in respiratory care is the effect of multiple factors. More studies are required to determine what those factors are and how they work (Gupta et al., 2024).

Boxplot analysis shows that the level of satisfaction significantly varies with the type and experience of the respondents which is relevant to the application of ML in practice. Low satisfaction among AIHCPs could be interpreted in terms of the perceived utility of AI tools in clinical processes or reluctance to consider AI-driven predictions (in targeted patients) as valid and reliable. For this reason, proper education and training are needed so that healthcare professionals can adapt to AI-assisted treatment. Moreover, the fact that there are outliers indicates that the experience of certain individuals with AI in respiratory care is wholly skewed in a positive or negative direction and if further investigated, could reveal specific interventions or issues responsible for the extreme cases (Afrifa-Yamoah et al., 2024).

5. CONCLUSION

This paper has sought to investigate the use of machine learning (ML) technology in the personalization of treatment plans for respiratory disorders concerning treatment effectiveness, satisfaction, and acceptance across the healthcare domain of professionals. The results indicate that machine learning is likely to change the future of respiratory care, but its actual use has some drawbacks. The level of satisfaction with AI-powered interventions is fairly low and varies across groups of healthcare professionals and data scientists who have different degrees of trust and experience with such technology.

The report showed that the subsequent satisfaction data did not follow a normal distribution, and the Cronbach alpha coefficients of the survey items were lower than the prescriptive threshold which calls for enhancement of the measurement devices. Furthermore, the average relationships among the relevant variables show that the linear concept of AI familiarity and satisfaction, which is AI as a single variable in the equation on satisfaction, was rational and in fact, there is a combination of factors that contribute to the disposition of ML in respiratory care rather than AI familiarity alone.

AI tools automated in most areas of medical imaging are associated with several risks that are not reflected by the reported cost-saving benefits. Clinical adoption is further hindered by practicing radiologists' concerns about the efficiency, reliability, and effectiveness of AI systems for real-world patients. Such narratives further reinforce the need for continued education, further training, and enhanced communication to build trust in AI-based solutions. Besides, future work may include attempts to investigate the extreme views of ML of those emotional defenders and haters, whose emotions seem to create more noise than evidence, as well as to improve and validate measures of sentiments in AI in healthcare.

To conclude, though machine learning opens up the possibility of developing tailored respiratory disorder management strategies for patients, such applications of machine learning must be treated with care. The primary emphasis should be placed on the interface of technology with existing healthcare continuously. Challenges of this nature must be addressed as a priority to ensure efficient respiratory resource applications across various healthcare environments.

REFERENCES

[1] Adeghe, E. P., Okolo, C. A., & Ojeyinka, O. T. (2024). The role of big data in healthcare: A review of implications for patient outcomes and treatment personalization. World Journal of Biology Pharmacy and Health Sciences, 17(3), 198-204.

[2] Afrifa-Yamoah, E., Adua, E., Peprah-Yamoah, E., Anto, E. O., Opoku-Yamoah, V., Acheampong, E., . . . Hashmi, R. (2024). Pathways to chronic disease detection and prediction: Mapping the potential of machine learning to the pathophysiological processes while navigating ethical challenges. Chronic Diseases and Translational Medicine.

[3] Agarwal, S. (2024). Machine Learning Based Personalized Treatment Plans for Chronic Conditions. Paper presented at the 2024 2nd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT).

[4] Ahmad, S., & Raza, K. (2024). An extensive review on lung cancer therapeutics using machine learning techniques: state-of-the-art and perspectives. Journal of Drug Targeting, 1-12.

[5] Ahmed, Z., Mohamed, K., Zeeshan, S., & Dong, X. (2020). Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. Database, 2020, baaa010.

[6] Al-Anazi, S., Al-Omari, A., Alanazi, S., Marar, A., Asad, M., Alawaji, F., & Alwateid, S. (2024). Artificial intelligence in respiratory care: Current scenario and future perspective. Annals of Thoracic Medicine, 19(2), 117-130.

[7] Alapati, N. K., & Valleru, V. (2023). Leveraging AI for Predictive Modeling in Chronic Disease Management. Innovative Computer Sciences Journal, 9(1).

[8] Bica, I., Alaa, A. M., Lambert, C., & Van Der Schaar, M. (2021). From real-world patient data to individualized treatment effects using machine learning: current and future methods to address underlying challenges. Clinical Pharmacology & Therapeutics, 109(1), 87-100.

[9] Boukhechba, M., Baglione, A. N., & Barnes, L. E. (2020). Leveraging mobile sensing and machine learning for personalized mental health care. Ergonomics in design, 28(4), 18-23.

[10] Chinni, B. K., & Manlhiot, C. (2024). Emerging analytical approaches for personalized medicine using machine learning in pediatric and congenital heart disease. Canadian Journal of Cardiology.

[11] Chmiel, F. P., Burns, D. K., Pickering, J. B., Blythin, A., Wilkinson, T. M., & Boniface, M. J. (2022). Prediction of chronic obstructive pulmonary disease exacerbation events by using patient self-reported data in a digital health app: statistical evaluation and machine learning approach. JMIR medical informatics, 10(3), e26499.

[12] Cohen, O., Kundel, V., Robson, P., Al-Taie, Z., Suárez-Fariñas, M., & Shah, N. A. (2024). Achieving Better Understanding of Obstructive Sleep Apnea Treatment Effects on Cardiovascular Disease Outcomes through Machine Learning Approaches: A Narrative Review. Journal of Clinical Medicine, 13(5), 1415.

[13] Deorankar, P. S., Vaidya, V. V., Munot, N. M., Jain, K. S., & Patil, A. R. (2024). Optimizing Healthcare Throughput: The Role of Machine Learning and Data Analytics. In Biosystems, Biomedical & Drug Delivery Systems: Characterization, Restoration and Optimization (pp. 225-255): Springer.

[14] Dhumale, A., Kakade, S., & Patil, V. Predictive Analytics in Precision Medicine Leveraging Machine Learning Algorithms for Personalized Diagnosis, Treatment Planning, and Patient Outcome Prediction.

[15] Feng, Y., Wang, Y., Zeng, C., & Mao, H. (2021). Artificial intelligence and machine learning in chronic airway diseases: focus on asthma and chronic obstructive pulmonary disease. International journal of medical sciences, 18(13), 2871.

[16] Flores, A. M., Demsas, F., Leeper, N. J., & Ross, E. G. (2021). Leveraging machine learning and artificial intelligence to improve peripheral artery disease detection, treatment, and outcomes. Circulation Research, 128(12), 1833-1850.

[17] Giansanti, D. (2024). Joint Expedition: Exploring the Intersection of Digital Health and AI in Precision Medicine with Team Integration. In (Vol. 14, pp. 388): MDPI.

[18] Godbin, A. B., & Jasmine, S. G. (2024). Leveraging Radiomics and Genetic Algorithms to Improve Lung Infection Diagnosis in X-Ray Images Using Machine Learning. IEEE Access.

[19] Gupta, M., Tanwar, S., Bharany, S., Binzagr, F., Osman, H. A., Ibrahim, A. O., & Karim, S. A. A. (2024). Revolutionizing Healthcare by Unleashing the Power of Machine Learning in Diagnosis and Treatment.

International Journal of Advanced Computer Science & Applications, 15(3).

[20] Hakami, M. A. (2024). Harnessing machine learning potential for personalized drug design and overcoming drug resistance. Journal of Drug Targeting, 32(8), 918-930.

[21] Husnain, A., Hussain, H. K., Shahroz, H. M., Ali, M., & Hayat, Y. (2024). A Precision Health Initiative for Chronic Conditions: Design and Cohort Study Utilizing Wearable Technology, Machine Learning, and Deep Learning. International Journal of Advanced Engineering Technologies and Innovations, 1(2), 118-139.

[22] Hussain, I., & Nazir, M. B. (2024). Precision Medicine: AI and Machine Learning Advancements in Neurological and Cardiac Health. Revista Espanola de Documentacion Cientifica, 18(02), 150-179.

[23] Ijaz, A., Nabeel, M., Masood, U., Mahmood, T., Hashmi, M. S., Posokhova, I., . . . Imran, A. (2022). Towards using cough for respiratory disease diagnosis by leveraging Artificial Intelligence: A survey. Informatics in Medicine Unlocked, 29, 100832.

[24] Isangula, K. G., & Haule, R. J. (2024). Leveraging AI and Machine Learning to Develop and Evaluate a Contextualized User-Friendly Cough Audio Classifier for Detecting Respiratory Diseases: Protocol for a Diagnostic Study in Rural Tanzania. JMIR Research Protocols, 13(1), e54388.

[25] Johnson, K. B., Wei, W. Q., Weeraratne, D., Frisse, M. E., Misulis, K., Rhee, K., . . . Snowdon, J. L. (2021). Precision medicine, AI, and the future of personalized health care. Clinical and translational science, 14(1), 86-93.

[26] Khanam, A., Masoodi, F. S., & Bamhdi, A. (2024). From data to insights: Leveraging machine learning for diabetes management. In A Biologist's Guide to Artificial Intelligence (pp. 97-123): Elsevier.

[27] Kumar, D., Pawar, P. P., Gonaygunta, H., Nadella, G. S., Meduri, K., & Singh, S. (2024). Machine learning's role in personalized medicine & treatment optimization. World Journal of Advanced Research and Reviews, 21(2), 1675-1686.

[28] Li, D., Abhadiomhen, S. E., Zhou, D., Shen, X.-J., Shi, L., & Cui, Y. (2024). Asthma prediction via affinity graph enhanced classifier: a machine learning approach based on routine blood biomarkers. Journal of Translational Medicine, 22(1), 100.

[29] Luz, A., & Ray, D. (2024). AI-Powered Disease Diagnosis: Evaluating the Effectiveness of Machine Learning Algorithms.

[30] Naik, K., Goyal, R. K., Foschini, L., Chak, C. W., Thielscher, C., Zhu, H., . . . Terranova, N. (2024). Current status and future directions: The application of artificial intelligence/machine learning for precision medicine. Clinical Pharmacology & Therapeutics, 115(4), 673-686.

[31] Oyebode, O., Fowles, J., Steeves, D., & Orji, R. (2023). Machine learning techniques in adaptive and personalized systems for health and wellness. International Journal of Human-Computer Interaction, 39(9), 1938-1962.

[32] Prabhod, K. J. (2022). The Role of Machine Learning in Genomic Medicine: Advancements in Disease Prediction and Treatment. Journal of Deep Learning in Genomic Data Analysis, 2(1), 1-52.

[33] Rahman, K., Pasam, P., Addimulam, S., & Natakam, V. M. (2022). Leveraging AI for Chronic Disease Management: A New Horizon in Medical Research. Malaysian Journal of Medical and Biological Research, 9(2), 81-90.

[34] Ramón, A., Bas, A., Herrero, S., Blasco, P., Suárez, M., & Mateo, J. (2024). Personalized Assessment of Mortality Risk and Hospital Stay Duration in Hospitalized Patients with COVID-19 Treated with Remdesivir: A Machine Learning Approach. Journal of Clinical Medicine, 13(7), 1837.

[35] Rasool, S., Husnain, A., Saeed, A., Gill, A. Y., & Hussain, H. K. (2023). Harnessing predictive power: exploring the crucial role of machine learning in early disease detection. JURIHUM: Jurnal Inovasi dan Humaniora, 1(2), 302-315.

[36] Rhodes, C. J., Sweatt, A. J., & Maron, B. A. (2022). Harnessing big data to advance treatment and understanding of pulmonary hypertension. Circulation Research, 130(9), 1423-1444.

[37] Shah, F. A., Meyer, N. J., Angus, D. C., Awdish, R., Azoulay, É., Calfee, C. S., . . . Leligdowicz, A. (2021). A research agenda for precision medicine in sepsis and acute respiratory distress syndrome: an official American Thoracic Society research statement. American journal of respiratory and critical care medicine, 204(8), 891-901.

[38] Shamji, M. H., Ollert, M., Adcock, I. M., Bennett, O., Favaro, A., Sarama, R., . . . Fontanella, S. (2023). EAACI guidelines on environmental science in allergic diseases and asthma–leveraging artificial intelligence and machine learning to develop a causality model in exosomes. Allergy, 78(7), 1742-1757.

[39] Shanmuga Sundari, M., Penthala, H. R., Mogullapalli, A., & Ammangatambu, M. M. (2024). AI-Based Personalized Drug Treatment. Artificial Intelligence and Machine Learning in Drug Design and Development, 369-406.

[40] Shukla, A. (2024). Revolutionizing Personalized Medicine: A Comprehensive AI Tool for Lung Cancer Severity Prediction and Treatment Recommendation (2516-2314). Retrieved from

[41] Singh, R., Lodhi, A. D., Mishra, A. K., Aeron, A., & Sharma, V. (2024). Predictive Lung Disease Identification Using Artificial Intelligence and Machine Learning Algorithm. Paper presented at the 2024 2nd International Conference on Disruptive Technologies (ICDT).

[42] Singhania, K., & Reddy, A. (2024). Improving preventative care and health outcomes for patients with chronic diseases using big data-driven insights and predictive modeling. International Journal of Applied Health Care Analytics, 9(2), 1-14.

[43] Tarumi, S., Takeuchi, W., Chalkidis, G., Rodriguez-Loya, S., Kuwata, J., Flynn, M., . . . Kramer, H. (2021). Leveraging artificial intelligence to improve chronic disease care: methods and application to pharmacotherapy decision support for type-2 diabetes mellitus. Methods of Information in Medicine, 60(S 01), e32-e43.

[44] Theodorakis, N., Feretzakis, G., Tzelves, L., Paxinou, E., Hitas, C., Vamvakou, G., . . . Nikolaou, M. (2024). Integrating Machine Learning with Multi-Omics Technologies in Geroscience: Towards Personalized Medicine. Journal of Personalized Medicine, 14(9), 931.

[45] Tsang, K. C., Pinnock, H., Wilson, A. M., & Shah, S. A. (2022). Application of machine learning algorithms for asthma management with mHealth: a clinical review. Journal of Asthma and Allergy, 855-873.

[46] Wang, C., Ma, J., Zhang, S., Shao, J., Wang, Y., Zhou, H.-Y., . . . Li, W. (2022). Development and validation of an abnormality-derived deep-learning diagnostic system for major respiratory diseases. NPJ digital medicine, 5(1), 124.

[47] Wesnawa, M. A. D. P., Asmara, O. D., & Supadmanaba, I. G. P. (2023). Emerging Role of Precision Medicine in Diagnosis and Treatment of Chronic Respiratory Disease.

[48] Woodman, R. J., Koczwara, B., & Mangoni, A. A. (2024). Applying precision medicine principles to the management of multimorbidity: the utility of comorbidity networks, graph machine learning, and knowledge graphs. Frontiers in Medicine, 10, 1302844.

[49] Wu, Y., & Wu, M. (2024). Biomedical Data Mining and Machine Learning for Disease Diagnosis and Health Informatics. In (Vol. 11, pp. 364): MDPI.

[50] Yadav, P., Rastogi, V., Yadav, A., & Parashar, P. (2024). Artificial Intelligence: A Promising Tool in Diagnosis of Respiratory Diseases. Intelligent Pharmacy.

[51] Zahra, M. A., Al-Taher, A., Alquhaidan, M., Hussain, T., Ismail, I., Raya, I., & Kandeel, M. (2024). The synergy of artificial intelligence and personalized medicine for the enhanced diagnosis, treatment, and prevention of disease. Drug Metabolism and Personalized Therapy, 39(2), 47-58.

[52] Zheng, L., Ohde, J. W., Overgaard, S. M., Brereton, T. A., Jose, K., Wi, C.-I., . . . Juhn, Y. J. (2024). Clinical Needs Assessment of a Machine Learning–Based Asthma Management Tool: User-Centered Design Approach. JMIR Formative Research, 8(1), e45391.