International Journal of Technology and Applied Science (IJTAS)

E-ISSN: 2230-9004 ● Website: www.ijtas.com ● Email: editor@ijtas.com

The Evolving Role of AI Models in Community-Acquired Pneumonia Risk Prediction and Management

Adellailluminata Shubila Ngambeki[1], Deepika Kapoor[2]

[1,2]Department of Medical Laboratory Technology, University Institute of Allied Health Sciences, Chandigarh University, Mohali-140413, Punjab, India.

Abstract:
Accurate risk assessment and prognostication are essential for optimizing treatment outcomes in community-acquired pneumonia (CAP). Over the years, multiple risk prediction models and severity scores have been developed and validated to enhance clinical judgment, including widely used tools such as PSI, CURB-65, DS CRB-65, PRS, CARPE DIEM, SOFA, qSOFA, SeF, SeF-ML, and NEWS-2. Refinements in these systems include modifications of traditional scoring methods, integration of novel biomarkers, and, more recently, the application of artificial intelligence (AI) and machine learning algorithms to improve predictive accuracy and clinical utility. This review emphasizes the potential of AI-driven approaches to strengthen clinical decision-making in CAP for both inpatient and outpatient management. Evidence from recent studies (2019–2025) highlights how AI can optimize risk stratification, refine prognostication, and ultimately improve patient outcomes across diverse populations with comorbidities. Nonetheless, significant hurdles remain, including model complexity, lack of generalizable trainable datasets, limited clinical integration, and ethical concerns. Addressing these challenges is imperative to fully harness AI as a transformative tool in CAP management.

Keywords: Artificial intelligence, Machine learning, community-acquired pneumonia (CAP), biomarkers, chest X-ray (CXR), electronic health record (EHR).

1. INTRODUCTION

Artificial intelligence handles tasks by machines that are usually linked with human intelligence. Machine learning enables computers to gain insight derived from data in the absence of specific programming. Building on established statistical approaches, ML keeps receiving an increasing amount of research interest in healthcare studies, owing to its aptitude for enhancing patient care along with disease prediction. Supervised learning is normally employed in healthcare epidemiological applications of machine learning. Four phases can be used to simplify the pipeline when creating ML software. (A) A prior data set featuring continuously obtained EHR information (such as vital signs, co-diagnosis, ED appearance, age, and gender) is compiled by researchers. (B) The computing system gains competence on how various patient parameters engage to foresee individual patients' aftermath by fitting a ration of this information- also known as initial data or train set—to one or additional algorithms. (C) A validation sample group is then employed to assess final model, and finally, a prototype with unparalleled fidelity, highest precision, and memory is selected. (D) Following training, the chosen model's anticipated results are assessed with actual patient outcomes using a test data set. If the model works efficiently, it can be applied in the future to guide treatment choices when coupled with clinical knowledge.[1]

Among various origins of hospital admissions, mortality, and steep medical fees, **CAP** is one that always goes unnoticed. Timely detection and determination of the ideal standard of care are crucial for upgrading aftereffects, given that manifestations can vary from a scope of slight ailment, one which can be addressed as an outpatient to a dire illness that needs treatment in the ICU. CAP is brought about by a variety of

microbes across different species of bacteria, viruses, and fungi. The most common are *Staphylococcus aureus, Streptococcus pneumoniae*, *Haemophilus influenzae*, *Enterobacteriaceae* like *Klebsiella pneumoniae*, *Chlamydia pneumoniae, Mycoplasma, Legionella*, *Chlamydia psittaci*, rhinovirus, SARS-CoV-2, and influenza.[2] It exhibits a multitude of symptoms with the key elements being illustrated in Fig.1 below, across all age groups.

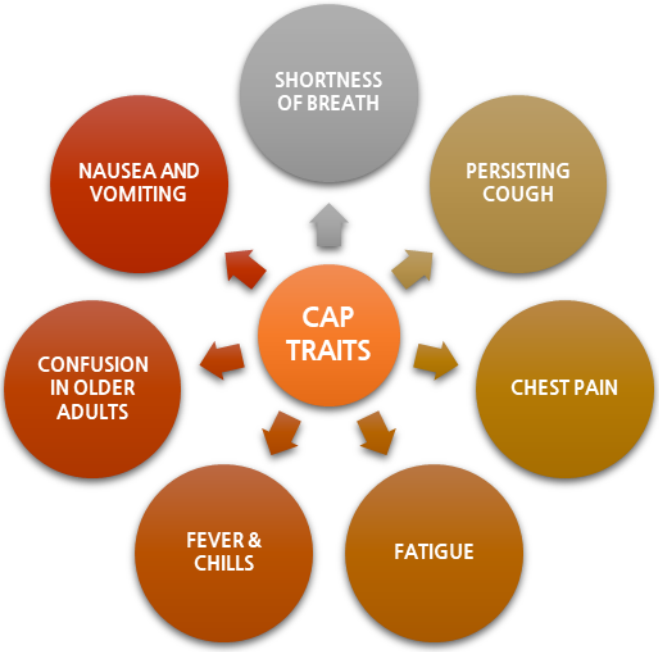

Fig.1 Illustration showing common symptoms associated with community acquired pneumonia

Although one-third of patients die after only a year of being released from healthcare centers due to pneumonia, community-acquired pneumonia tends to be overlooked by the general public as a high-priority issue. Strong data on managing CAP in the world population is lacking, although a significant number of patients that were hospitalized had no less than one immunosuppressive determinant globally. To lower the deaths, illnesses, and hurdles associated with CAP in individuals that possess both strong and weak immunity, various clinical care points should be addressed. Quick detection, pathological assessment, early detection and supervision of convolutions (such as ventilatory collapse, septicemia, and multiple organ dysfunction), broad-spectrum antibiotic treatment founded on patient risk determinants and localized microbial public health studies, customized antimicrobial treatment derived from pathological data, suitable results for curative transition from intravenous to oral antimicrobials, transition planning, and extended monitoring are some of those aspects.[3]

Imaging and blood work will be part of the initial workup for pneumonia. If a lesion or effusion is identified, chest x-rays will be required to increase the accuracy of the detection techniques. An absolute blood count with differentials should encompass part of the bloodwork; serum electrolytes along with liver and kidney function tests assist in confirming signs of inflammation and assess its level of severity. It is advised to get screened for influenza in the winter. If accessible, molecular techniques for testing nasopharyngeal swabs for respiratory viruses may be taken into consideration. Blood cultures and sputum cultures ought to be obtained from admitted patients, preferably prior to administration of antibiotic medication; however, treatment should not be delayed.[2]

1.1. Limitations of Current Methods.

At the moment, there are many elements related to patient care and medical history, making it difficult to understand what is happening to patients. Keeping up with the latest developments in medicine is very challenging due to the continuous expansion of medical research and advancement in automated diagnostic tools. Currently, there is immense medical knowledge that a single person could never read

throughout their lifespan. Large volumes of data will inevitably accumulate as a result of medical difficulties such as a fast-growing population and a more complicated medical history each passing decade.[4]

Current clinical procedures, however, have doctors making choices based upon their own and their team's experiences, as well as research studies carried out with inadequate data or treatment recommendations, render the results obtained deficient due to lack of universality. It would be worthwhile to think about integrating AI/ML into healthcare and infectious disease risk management if doctors want to handle obstacles more successfully and effectively

1.2. Driving Forces for AI Use in Healthcare Setting

Two important forces have driven the idea to use and integrate AI/ML in healthcare from risk prediction, diagnosis, and treatment to management of diseases.

- The first force is huge data availability, meaning that a lot of data can be instantly accessible from EHRs. In contrast, earlier methods of data collection necessitated the use of conventional clinical recorders that were not easily traceable.
- The second force is enhanced computer performance. These days, computer systems run quickly and have a large capacity for processing information quickly. The vast amount of clinical data we hold can be used by these computer-driven mathematical techniques to forecast various clinical scenarios.

The ease of use of computerized systems is the key component for integrating AI to assist in clinical decision-making and treatment recommendations.

2. EMPIRICAL EVIDENCE ON PREDICTION MODELS

Information about the application of AI to enhance community-acquired pneumonia care increases by the day. By using “Community acquired pneumonia risk prediction scores” as a search phrase. Among 313 papers that came out from the search, research papers from 2019 to date that provided information regarding the AI methods employed and successfully validated in predicting instances of CAP were spatially selected with some included in this literature review. Up until recently, the majority of AI has been employed to diagnose pneumonia by analyzing chest X-ray (CXR) patterns, among other parameters. In the last few years ground breaking innovative algorithms have been developed and assessed by numerous scientists and medical professionals all around the world as seen in **Table 1**. below.

Table 1. Literature On Existing Prediction Models and Machine Learning Algorithms from the Year 2019 To 2022

Authors	Year	Investigation	Findings	Reference
Ehsanpoor et al.	2019	validated the SMART-COP score for predicting the severity and outcomes of CAP in the emergency department.	The study demonstrated an impressive accuracy and precision, proving to be a valid algorithm.	[5]
Gallagher et al.	2020	constructed a multivariable model for predicting mortality in HIV-negative children with severe pneumonia in low- and middle-income countries.	They found that the frequency of WHO danger signs was the best predictor of mortality and it may be one of the most practical measure accessible to support the medical treatment of CAP cases.	[6]
Kang et al.	2020	Comparison of CURB-65 model to machine learning models in predicting the 30-	The study found that machine learning models could more accurately	[7]

		day death rate of pneumonia patients and their admission in the ICU.	predict the 30-day death rate of pneumonia patients and the need for ICU admission compared to the CURB-65 model with significant statistics.	
Carmo et al.	2021	Conducted an evaluation of multiple severity scores and developed a Pneumonia Shock Score for predicting death rate in CAP patients.	They examined severity scores for predicting mortality in critically ill CAP patients in a Brazilian ICU and developed a Pneumonia Shock Score that outperformed existing scores like SAPS 3, CURB-65, CRB-65, and qSOFA.	[8]
Quah et al.	2021	Created an AI model based on chest X-rays (CAPE).	The study found that it enhanced discrimination when coupled with conventional severity scores like PSI and CURB-65.	[9]
Florin et al.	2021	Developed a prediction model to risk stratify children with suspected CAP.	The prediction model was able to successful guide hospital admission recommendations by offering personalized risk assessments that, when combined with clinical judgment, enhanced the treatment of kids who may have CAP.	[10]
Rhodes et al.	2022-2023	Created models predicting the likelihood of MRSA CAP in admitted patients.	They utilized machine learning to create models predicting the likelihood of MRSA CAP in admitted patients specifically within 72 hours of admission which showcased great accuracy.	[11]

2.1. Current Studies on CAP Prediction Algorithms

In January 2023, Catia Cilloniz et al., conducted a study to evaluate whether a CPN model better predicted the mortality rate in CAP patients than the commonly used prediction model. Two university hospitals in Spain were the sites of their derivation-validation retrospective study. “A CPN's ability to predict 30-day death rate was evaluated and contrasted with supplementary scoring models, including CURB-65, SOFA, qSOFA, and PSI. SepsisFinder (SeF) was created to foresee the death rate in sepsis, and SeF-ML was modified for CAP. The software for the SeF models was proprietary. The DeLong approach for correlated ROC was used to evaluate their variation. There were 1,034 patients in the test sample group and 4,531 patients in the training sample group. The 30-day mortality prediction AUC of SeF-ML in the test sample group was consistent with the training data's AUC with significant P value of 0.51. Compared to CURB-65 and qSOFA, SeF-ML's AUC was noticeably higher. It didn’t, however, deviate much from those of

SOFA and PSI." Using structured health data, SeF-ML showed the capability to boost death prognosis for individuals with CAP. To bolster generalizability, more external validation research ought to be carried out.[12]

In July 2023, Eun Tae Jeon et al., conducted a study to create and authenticate ML models for forecasting death in individuals suffering from acute pneumonia. Individuals with pneumonia whom were hospitalized in the intensive care unit between January 2016 and December 2021 were assessed in their retrospective analysis. "By contrasting AUROC of machine learning models with that of traditional severity-of-infection scoring systems, the predictive performance was examined. Three machine learning models were assessed: multilayer perceptron (MLP), gradient-boosted decision trees (LightGBM), and logistic regression with L2 regularization. 223 (27.3%) of the 816 pneumonia patients who were included passed away." All machine learning models performed considerably higher than the Simplified Acute Physiology Score II. The LightGBM and MLP models outperformed the logistic regression model in terms of reclassification in analysis for NRI. To sum up, the ML models performed exceptionally well in forecasting in-ICU death rate for patients suffering from pneumonia. Additionally, their work emphasized the possible benefits of using distinct machine learning models to forecast in-ICU mortality across various categories.[13]

In April 2024, Moritz Müller-Plathe et al., conducted a study on the existing severity scores in kidney transplant recipients due to decreased prognostic values of these prediction scores for this stratum of patients. "They looked back over 310 KTR's initial CAP occurrences following kidney transplantation. So as to predict severe pneumonia and admitted individuals' death rate, they evaluated medical manifestations and authenticated 8 distinct severity scores (CRB-65, CURB-65, DS-CRB-65, qSOFA, SOFA, PSI, IDSA/ATS minor criteria, and NEWS-2). Up to 48 hours following admission, risk ratings were evaluated; however, they were always done before an endpoint. To deal with missing values, multiple imputation was used. Overall, 48 patients (15.5%) experienced severe pneumonia, and 16 out of 310 patients (5.2%) passed away. SOFA and NEWS-2 were the strongest predictors of severe pneumonia as observed in ROC analysis, with significant AUC values" The best tools for identifying KTR who have high chances for developing CAP are SOFA and NEWS-2. Since even individuals with a score of zero have a 7% chance of developing severe pneumonia, CRB-65 was excluded as an accurate score for direct outpatient treatment in KTR patients as opposed to immunocompetent patients.[14]

In July 2024, Yoon-Hee Choi et al., examined the use of chest CT scan thoracic muscle mass as a molecular marker to forecast medical aftereffects in intensive care unit individuals suffering from acute pneumonia. "Thoracic muscle mass was measured using AI-enhanced 3D segmentation on chest CT images and electronic medical data of 778 intensive care unit patients with severe CAP between January 2016 and December 2021. Muscle mass profiles from CAT scans were employed to group patients into clusters, and impact of these clusters on medical manifestations, including in-hospital death rate and extubation success, were evaluated. Higher muscle mass (Cluster 1) was linked to better medical manifestations such as successful extubation and decreased in-hospital death rate (8% vs. 29% in Cluster 3), according to the study's three clusters. The model that integrated muscle mass measures performed better than traditional evaluations." These results demonstrated how well muscle mass assessment predicts outcomes compared to indices like APACHE II and SOFA. AI-assisted chest CT analysis of thoracic muscle mass offered a promising predictive strategy for severe pneumonia, supporting its incorporation into medical practice for improved aftermath forecasting and individualized clinical care.[15]

In January- February 2025, Sriram Ramgopal et al., prospectively assessed the effectiveness of two prediction models CARPE DIEM models and PRS models using a sample of kids aged 90 days to 18 years who were receiving chest radiography for suspected pneumonia in a pediatric ED between January 1 of 2022, and December 31st of 2023. "Using the initial intercepts and coefficients, they assessed the model's performance and also looked for variations in performance during the recalibration and re-estimation phases. 92 (41.0%) of the 202 patients they included had radiographic pneumonia; their midpoint age was 3 years, with IQR of 1-6 years. When utilizing appropriate cut points, the PRS model

outperformed CARPE DIEM model in terms of accuracy and precision. Model performance was enhanced by recalibration and re-estimation, especially for CARPE DIEM model, which showed improvements in calibration together with accuracy and precision." They concluded that when it came to radiographic pneumonia prediction, PRS model outperformed CARPE DIEM model. These models did not perform well enough among kids with a soaring prevalence of pneumonia to be applied without consulting a clinician. Their results showed that to increase the models' usefulness, more validation and development are required. [16]

In February 2025, Aaditeya Jhaveri et al., tested an externally built AI tool for predicting disposition using chest X-rays (CXR) in individuals with CAP in the ED in a shadow deployment. To inform deployment decisions, both retrospective and prospective external validations were carried out to evaluate the differences between the two evaluations and across subgroups. "The CNN was prospectively verified on 3062 'suspected-CAP' patients from January 1 to January 31, 2023, and retrospectively validated using 17689 patients from November 1, 2020, to June 30, 2021. AUC, accuracy, precision, PPV, and NPV were among the calibration and standard metrics that were computed. For age, sex, modality, and CXR projection (PA vs. AP), subgroup analyses were performed. The study's performance in both retrospective and prospective validations was modest and steady with minimal contrast. Despite the encouraging agreement, more direct comparisons were said to be required to ascertain whether both validation procedures are required in various clinical scenarios. According to the subgroup study, the tool might help older patients (high PPV) be admitted more quickly and younger patients (high NPV) be discharged more quickly.[17]

A summary of the above studies, which either evaluated various prediction algorithms, created algorithms, or validated and added more parameters to existing models in the last 3 years is shown in Fig.2 below.

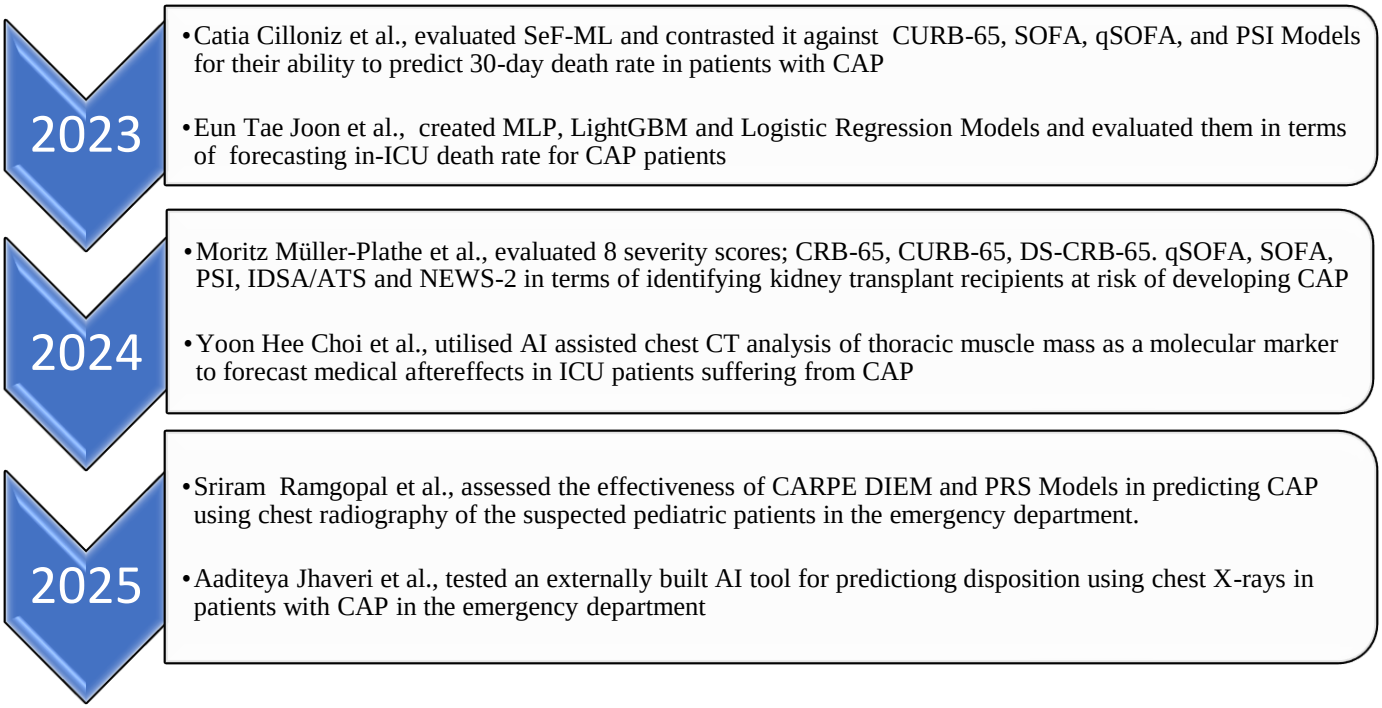

Fig.2 Illustrative summary of current research on AI prediction tools created and validated across a diverse group of patients utilizing multiple parameters to enhance the model's accuracy and precision.

3. DISCUSSION

In evaluating the gravity of CAP and forecast patient outcomes, traditional severity scores like the Pneumonia Severity Index (PSI), CURB-65 (Confusion, Urea, Respiratory rate, Blood pressure, Age ≥ 65 years), and CRB-65 (Confusion, Respiratory rate, Blood pressure, Age ≥ 65 years) have been used

extensively.[8] Although simple to use, the CURB-65 and CRB-65 ratings might not fully reflect the complexity of CAP in some patient populations. For instance, they might not be able to forecast death in individuals who are seriously unwell or who have a lot of comorbidities.[8] CRB-65 was proved not to be efficient in directing outpatient treatment in kidney transplant recipient (KTR) individuals.[14] To enhance risk stratification in CAP, researchers have looked into the application of new biomarkers and imaging methods in addition to improving conventional scoring systems. Procalcitonin (PCT) is an inflammatory marker that has been investigated as a possible means of directing antibiotic treatment and distinguishing between bacterial and viral pneumonia. Its usefulness in forecasting death or other unfavorable events in CAP is still debatable, nevertheless.[4] Another inflammatory marker that is frequently employed in clinical practice is C-Reactive Protein (CRP). Although higher CRP levels are linked to more severe CAP, they may not always accurately predict death or ICU admission.[4] Yoon-Hee Choi et al. (2024) looked at the capability to utilize thoracic muscle mass as a molecular marker to foresee medical manifestation in intensive care unit individuals with severe CAP. They assessed this mass using AI-enhanced 3D segmentation on chest CT images, with higher muscle mass associated with improved clinical outcomes.[15]

Numerous studies have concentrated on creating risk models tailored to pediatric populations because of the special traits and difficulties associated with treating CAP in children. To risk classify and guide hospital admission recommendations for children with suspected CAP, Todd A. Florin et al. (2020) created and validated a prediction model within the Pediatric Emergency Care Applied Research Network (PECARN). The model had readily available variables like oxygenation, systolic blood pressure, respiratory rate, and radiographic results.[10] Two forecasting models, the Pneumonia Risk Score (PRS) models and the Catalyzing Ambulatory Research in Pneumonia Aetiology and Diagnostic Innovations in Emergency Medicine (CARPE DIEM) models, were prospectively evaluated by Sriram Ramgopal et al. (2025) for their ability to foresee radiographic pneumonia in children. The PRS model fared greater compared to the CARPE DIEM model, according to the study, however, both models needed more research and improvement to increase their clinical usefulness.[16]

3.1. Challenges And Future Directions

Even though risk prediction models for CAP have advanced significantly, there are still many obstacles to overcome.

- **Generalizability**: A large number of prediction models are created and tested in certain healthcare settings or populations, which may restrict their applicability in other situations. To make sure that these models are reliable and applicable, external validation in a variety of populations is essential.
- **Data Availability and Quality**: The completeness and quality of the statistics utilized to train and verify prediction algorithms/models determine their accuracy. To create accurate and clinically useful prediction systems, efforts must be made to enhance data gathering and standardization.
- **Integration into Clinical Practice:** Without successful integration into clinical practice, even the most precise prediction models have little utility. It is necessary to develop methods to make these models easier to use and implement, such as integrating them into medical decision support algorithms and EHRs.
- **Ethical Issues**: Bias, accountability, and openness are some of the ethical issues raised by the application of AI in healthcare. It is crucial to make sure that professionals maintain ultimate accountability for patient care and that prediction models are created and applied fairly and equally.

4. CONCLUSION

Overall, a lot of researchers have attempted to improve risk prediction in CAP using a variety of approaches, such as sophisticated machine learning algorithms, improved biomarkers, and conventional scoring systems. The incorporation of novel biomarkers and AI-driven models holds promise for enhancing the precision and customization of risk assessment despite the drawbacks of conventional severity scores. Additionally, pediatric populations have seen the development and validation of specific risk models that improve clinical decision-making for children suspected of having CAP. These

developments highlight how crucial it is to improve and validate prediction systems to maximize CAP management and results for a variety of patient populations.

Statements and Declarations

Ethics Approval and Consent to Participate

Not applicable. This study is a review of previously published literature and did not involve the collection of new data from human participants or animals. All studies discussed were previously published and conducted in accordance with the Declaration of Helsinki and relevant institutional/national guidelines.

Consent to Participate

Not applicable. No human participants were directly involved in this review.

Approval Committee / Institutional Review Board (IRB)

Not applicable. No new human or animal data were collected; hence, approval from an ethics committee or IRB was not required.

Consent for Publication

Not applicable. This review does not contain identifiable personal data.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Clinical Trial Registration

Clinical trial number: not applicable.

Human Ethics and Consent to Participate Declarations

Human Ethics and Consent to Participate declarations: not applicable.

Competing Interests/ Conflict of Interests

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

REFERENCES:

[1] A. J. Hamilton *et al.*, "Machine learning and artificial intelligence: Applications in healthcare epidemiology," Oct. 2021, *Antimicrob Steward Healthc Epidemiol*. doi: 10.1017/ash.2021.192.

[2] H. Regunath and Y. Oba, "Community-Acquired Pneumonia," *StatPearls*, Jan. 2024.

[3] S. Aliberti, C. S. Dela Cruz, F. Amati, G. Sotgiu, and M. I. Restrepo, "Community-acquired pneumonia," Sep. 2021, *Lancet*. doi: 10.1016/S0140-6736(21)00630-9.

[4] A. Ito and T. Ishida, "Diagnostic markers for community-acquired pneumonia," *Ann. Transl. Med.*, vol. 8, no. 9, pp. 609–609, May 2020, doi: 10.21037/atm.2020.02.182.

[5] B. Ehsanpoor, E. Vahidi, J. Seyedhosseini, and A. Jahanshir, "Validity of SMART-COP score in prognosis and severity of community acquired pneumonia in the emergency department," *Am. J. Emerg. Med.*, vol. 37, no. 8, pp. 1450–1454, Aug. 2019, doi: 10.1016/j.ajem.2018.10.044.

[6] K. E. Gallagher *et al.*, "The Predictive Performance of a Pneumonia Severity Score in Human Immunodeficiency Virus-negative Children Presenting to Hospital in 7 Low- and Middle-income Countries," *Clin. Infect. Dis.*, vol. 70, no. 6, pp. 1050–1057, Mar. 2020, doi: 10.1093/cid/ciz350.

[7] S. Y. Kang *et al.*, "Predicting 30-day mortality of patients with pneumonia in an emergency department setting using machine-learning models," *Clin. Exp. Emerg. Med.*, vol. 7, no. 3, pp. 197–205, Sep. 2020, doi: 10.15441/ceem.19.052.

[8] T. A. Carmo *et al.*, "Derivation and Validation of a Novel Severity Scoring System for Pneumonia at Intensive Care Unit Admission," *Clin. Infect. Dis.*, vol. 72, no. 6, pp. 942–949, Mar. 2021, doi: 10.1093/cid/ciaa183.

[9] J. Quah *et al.*, "Chest radiograph-based artificial intelligence predictive model for mortality in

community-acquired pneumonia," *BMJ Open Respir. Res.*, vol. 8, no. 1, Aug. 2021, doi: 10.1136/bmjresp-2021-001045.

[10] T. A. Florin *et al.*, "Development and Internal Validation of a Prediction Model to Risk Stratify Children with Suspected Community-Acquired Pneumonia," *Clin. Infect. Dis.*, vol. 73, no. 9, pp. E2713–E2721, Nov. 2021, doi: 10.1093/cid/ciaa1690.

[11] N. J. Rhodes *et al.*, "Machine Learning to Stratify Methicillin-Resistant Staphylococcus aureus Risk among Hospitalized Patients with Community-Acquired Pneumonia," *Antimicrob. Agents Chemother.*, vol. 67, no. 1, Jan. 2023, doi: 10.1128/aac.01023-22.

[12] C. Cilloniz *et al.*, "Machine-Learning Model for Mortality Prediction in Patients With Community-Acquired Pneumonia: Development and Validation Study," *Chest*, vol. 163, no. 1, pp. 77–88, Jan. 2023, doi: 10.1016/j.chest.2022.07.005.

[13] E. T. Jeon *et al.*, "Machine learning-based prediction of in-ICU mortality in pneumonia patients," *Sci. Rep.*, vol. 13, no. 1, Dec. 2023, doi: 10.1038/s41598-023-38765-8.

[14] M. Müller-Plathe *et al.*, "Validation of risk scores for prediction of severe pneumonia in kidney transplant recipients hospitalized with community-acquired pneumonia," *Infection*, vol. 52, no. 2, pp. 447–459, Apr. 2024, doi: 10.1007/s15010-023-02101-z.

[15] Y. H. Choi *et al.*, "Cluster analysis of thoracic muscle mass using artificial intelligence in severe pneumonia," *Sci. Rep.*, vol. 14, no. 1, Dec. 2024, doi: 10.1038/s41598-024-67625-2.

[16] S. Ramgopal, M. Neveu, D. Lorenz, J. Benedetti, J. Lavey, and T. A. Florin, "External validation of two clinical prediction models for pediatric pneumonia," *Acad. Pediatr.*, vol. 25, no. 1, Jan. 2024, doi: 10.1016/j.acap.2024.08.009.

[17] A. Jhaveri, F. Abolhassani, and B. Fine, "Prospective External Validation of an AI-Based Emergency Department Pneumonia Disposition Prediction Tool.," *Can. Assoc. Radiol. J.*, p. 8465371251320938, Feb. 2025, doi: 10.1177/08465371251320938.