

Recent Advances in the Assessment Methods and Indicators for the Severity of Severe Pneumonia

Fei Li¹, Jun Li², Wei Xiao^{3*}

¹Department of Emergency Medicine, The First Affiliated Hospital of Yangtze University, Jingzhou, China

²Jingzhou City Emergency Medical Center, Jingzhou, China

³Department of Respiratory Medicine, The First Affiliated Hospital of Yangtze University, Jingzhou, China

Email: *2037282869@qq.com

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Abstract

As a fatal respiratory disease, accurate assessment of the severity of severe pneumonia is of great significance for clinical treatment and prognosis. In recent years, with the development of biomarkers, imaging technology and artificial intelligence, significant breakthroughs have been made in the assessment of severe pneumonia. This article systematically reviews the clinical scoring system of severe pneumonia, the application of new biomarkers, the innovation of imaging technology, and the role of artificial intelligence and big data, analyzes the advantages and limitations of the existing assessment methods, and looks forward to the future direction of the research, so as to provide a scientific basis for clinical practice and scientific research.

Keywords

Severe Pneumonia, Severity Assessment, Biomarkers, Imaging Techniques, Artificial Intelligence

1. Introduction

Globally, severe pneumonia is one of the leading causes of hospitalization and death, with a significant increase in morbidity and mortality, especially among the elderly, immunocompromised, and patients with underlying diseases [1] [2]. Accurate assessment of the severity of severe pneumonia plays a decisive role in the management of the disease, not only directly affecting the grading of the patient and the decision of whether or not to hospitalize or transfer the patient to an In-

*Corresponding author.

tensive Care Unit (ICU) for treatment, but also being closely related to the choice of treatment strategies and prognosis judgments [3].

In the early stage, the assessment of severe pneumonia mainly relies on clinical symptoms and laboratory indicators. Although the traditional clinical scoring system is convenient to operate, it has obvious deficiencies in dynamic assessment and individualized accurate assessment. Sun Zhen [4] *et al.* pointed out that when assessing the severity of the disease in patients with multiple comorbidities, the CURB-65 scoring system (including impaired consciousness, blood urea nitrogen, respiratory rate, blood pressure, and age ≥ 65 years) may underestimate the severity of the disease, especially in elderly patients aged 80 years and above, and the predictive efficacy of the scoring system is poor, which makes it difficult to accurately reflect the patient's true condition. The Pneumonia Severity Index (PSI), although it integrates a variety of comorbidities and laboratory indicators, is difficult to apply quickly in emergency situations due to its complexity [5].

In recent years, with the continuous emergence of biomarkers, imaging techniques, pathogenetic analysis, and multimodal integration methods, the assessment tools for severe pneumonia have become increasingly abundant [6] [7], meanwhile, the rapid development of artificial intelligence technology and the accumulation of medical big data have brought new opportunities for the assessment of severe pneumonia severity. Driven by global epidemics such as novel coronavirus pneumonia (Coronavirus Disease 2019, COVID-19), a large number of studies have been devoted to applying integrated assessment methods to address the complex multifactorial pathomechanisms of the disease [8]. These emerging techniques have significantly improved the accuracy of assessment and laid a solid foundation for the development of personalized treatment plans. The aim of this study is to systematically review the research progress of assessment methods for severe pneumonia, deeply analyze the characteristics of each assessment method, explore the future research direction, and provide theoretical references for clinical practice and scientific research.

2. Clinical Scoring System

The assessment of severe pneumonia relies heavily on a series of clinical criteria that are categorized into primary and secondary criteria [9]. These criteria are widely used in clinical practice to determine the severity of the disease and to guide treatment decisions. Although the commonly used scoring systems PSI and CURB-65 can reflect the severity of the disease [10], their complexity and lack of sensitivity to the early stage of the disease limit their application in clinical practice. The PSI scoring system is more complex, including multiple variables such as age, comorbidities, laboratory findings, etc., which can comprehensively reflect the severity of the patient's pneumonia but requires more time to calculate and analyze the severity of the disease in clinical practice. More time consuming to calculate and evaluate [5]. In contrast, the CURB-65 scoring system, despite its ease of use, may not be as predictive as the PSI score [4]. Studies have shown that the Systolic Blood

Pressure, Multilobar Involvement, Albumin, Respiratory Rate, Tachycardia, Confusion, Oxygen, and pH scoring method (Confusion, Oxygen, and pH, or SMART-COP) has significant advantages in predicting the need for mechanical ventilation or vasoactive medications in the assessment of younger patients or specific high-risk groups (e.g., pregnant women) [11], but its application still requires a large amount of laboratory data and its generalizability is limited compared to other scoring systems. Sequential Organ Failure Assessment Score (SOFA) is a scoring system for dynamic assessment of organ dysfunction, which has been widely used in the prognostic assessment of patients with severe pneumonia in recent years [12]. Zhang Kang [13] and other scholars showed that the SOFA score was superior to the CURB-65 score and the PSI score in predicting 28-day mortality in patients with severe pneumonia. Each of the current scoring systems has its own strengths and limitations, and it is recommended that the appropriate assessment tool be selected according to the different clinical settings and patient characteristics. For outpatients, the CURB-65 score or the Quick Sequential Organ Failure Assessment (qSOFA) may be preferred for rapid stratification. When assessing the prognosis of a child in the inpatient unit, PSI is more appropriate. For patients in the ICU, the SMART-COP scoring system has shown unique advantages in guiding treatment strategies.

3. Progress in Biomarker Research

3.1. Application of Procalcitonin (PCT) and C-Reactive Protein (CRP)

PCT is a non-hormonally active glycoprotein with extremely low concentrations in healthy individuals, which is significantly elevated when bacterial infections occur, and is therefore widely used in the diagnosis of bacterial infections and in the assessment of the severity of infections [14]. Jing L [15] *et al.* have found that elevated PCT is an independent risk factor for death within 30 days in patients with severe pneumonia, and that it has a good predictive value of morbidity and mortality. He Meng [16] *et al.* revealed that there was a significant correlation between elevated PCT levels and the severity of disease in patients with severe pneumonia, and that continuous monitoring of PCT levels had a higher value in predicting prognosis than single measurements, and was more effective in assessing the effectiveness of treatment.

CRP, an acute-phase response protein, is synthesized primarily by liver cells, and its concentration rises rapidly after the onset of bacterial infection and usually peaks within 24 to 48 hours [17]. The rise in CRP levels during the early stages of infection makes it a common and important indicator for assessing the activity of inflammation. CRP levels are usually low in viral infections (peak around 15.4 mg/L), whereas in gram-negative bacteremia, peak CRP levels can be as high as 140.9 mg/L [18]. In severe pneumonia, CRP can be used for early monitoring of the inflammatory response and identification of the type of infection. Zhuo Zhi Luying [19] *et al.* showed that the elevated levels of PCT and CRP are closely related to the

severity of infection, and the combination of these tests can provide a reliable basis for early diagnosis.

3.2. Neutrophil to Lymphocyte Ratio (NLR) and Platelet-to-Lymphocyte Ratio (PLR)

NLR and PLR, as novel inflammatory indicators, can reflect the immune status and inflammatory response of the body, which is important for the early diagnosis and prognostic assessment of severe pneumonia. Xinyi Fu [20] *et al.* demonstrated that the NLR ratio not only reflected the changes in the number of neutrophils and lymphocytes, but also revealed an immune imbalance caused by excessive activation of neutrophils. Yogesh Sharma [21] *et al.* found that NLR was effective as an independent predictor of adverse clinical outcomes in a population of patients with community-acquired pneumonia (CAP), as evidenced by prolonged hospitalization, increased risk of ICU admission, and increased in-hospital mortality. Studies by scholars such as Zhang Furong [22] revealed that PLR was significantly elevated in patients with severe pneumonia and showed a correlation with the severity of the disease, and in a study targeting severe *Mycoplasma pneumoniae* pneumonia, the optimal cut-off value of PLR was determined to be 97.47, with a sensitivity of 88.5% and a specificity of 69.4%, while the area under the curve (AUC) was 0.7%. (AUC) was 0.767. Although NLR and PLR have demonstrated some value in the diagnosis and prognostic assessment of severe pneumonia, their results are susceptible to the interference of various factors, such as age, gender, nutritional status, and immune function, and thus need to be comprehensively evaluated in combination with other indexes in the clinical application [23].

3.3. Red Blood Cell Distribution Width (RDW) and Interleukin-6 (IL-6)

RDW and IL-6 are closely associated with the progression and prognosis of severe pneumonia, and IL-6 in particular is valuable in predicting extrapulmonary complications. In recent years, RDW has been found to be associated with a variety of inflammatory diseases, and its elevation suggests the presence of chronic inflammation or oxidative stress in the body [24]. A study found that RDW levels were significantly elevated in patients with severe pneumonia, especially in those requiring ICU care and longer hospitalization [25], which showed a significant positive correlation between increased RDW and higher complication rates and mortality. In a study of critically ill COVID-19 patients, researchers found that elevated IL-6 levels were strongly associated with poorer prognosis in patients with severe pneumonia, that increased IL-6 levels showed a significant positive correlation with higher mortality, prolonged hospitalization, and more severe complications, and that IL-6 levels could be used as an adjunctive biomarker for assessing the prognosis of patients [26]. IL-6 has significant predictive value in predicting the development of extrapulmonary complications in patients with severe pneumonia. In patients with Severe Fever with Thrombocytopenia Syndrome (SFTS), there was a significant positive

correlation between IL-6 levels and various inflammatory markers and metabolic markers, and it was an independent predictor of disease severity and prognosis, in addition, elevated IL-6 levels were associated with acute kidney injury (Acute Kidney Injury). Acute Kidney Injury (AKI), the need for mechanical ventilation, and a significant increase in the risk of early death. [27]

4. Use of Imaging Techniques in Assessment

Imaging evaluation plays a crucial role in the diagnosis and severity assessment of severe pneumonia. Traditional imaging methods such as chest X-ray and CT have been widely used, while in recent years, new technologies such as ultrasound and quantitative image analysis have been added to enhance the value of imaging in guiding therapeutic decision-making and predicting prognosis.

4.1. Chest X-Ray, Computed Tomography Scan (CT) of the Chest, Lung Ultrasound (LUS)

Chest X-ray is a commonly used primary screening tool to quickly identify the presence and extent of pneumonia, and its low cost, ease of use, and sensitivity to acute lesions make it particularly suitable for low-resource settings. However, due to its limited resolution, it is easy to miss small lesions or overlapping lesions [28]. However, due to its limited resolution, chest X-ray tends to miss small lesions or overlapping foci and may not accurately identify early or mild lung lesions, especially in complex cases [29]. Chest CT technology allows a comprehensive assessment of the extent and severity of lung lesions and provides detailed information on lung structure. CT scans can clearly show inflammation, exudates, solid lesions, and the presence of complications (e.g., pleural effusions or lung abscesses) in the lungs. In a study of Chlamydia psittaci pneumonia [30], CT scans showed a variety of manifestations and dynamics of lung lesions, and the CT imaging features covered solid lesions in the lobes of the lungs, thickening of the interlobular septa, ground-glass shadows, and pleural effusions, which were closely correlated with the severity of the disease. Correlation. Another study emphasized the important role of CT in the evaluation of severe pneumonia, especially in identifying the extent and severity of lung lesions, which can help in early diagnosis of the lesions and enable dynamic monitoring of changes in the disease [31]. The LUS technique is able to rapidly assess the severity of lung lesions and effectively detect pathologies such as pleural effusion, lung solidity, and pulmonary edema. In addition, the noninvasive and reproducible nature of ultrasonography makes it possible to monitor changes in the condition in real time and to detect potential complications in a timely manner. In the Acute Respiratory Distress Syndrome (ARDS) patient population, LUS has become one of the diagnostic criteria for evaluating imaging changes in the lungs and has shown good correlation and feasibility compared with CT scanning in bedside evaluation [32].

4.2. Imaging Combined with Other Assessment Methods

LUS combined with PCT levels can effectively differentiate the etiology of pneu-

monia, and studies have shown that small, multiple pulmonary solid changes are commonly associated with viral pneumonia, whereas larger pulmonary solid changes are more likely to be associated with bacterial infections; dynamic air bronchial signs are usually suggestive of bacterial pneumonia, whereas static air bronchial signs are more commonly associated with viral infections [33]. Bacterial pneumonia is more likely to be suggested when LUS shows solid lung lesions and PCT levels >1 ng/ml [34]. The Procalcitonin and Lung UltraSonography-based antibiotic therapy in patients with Lower rESpiratory tract infection in the Swiss Emergency Departments, PLUS-IS-LESS) in assessing the potential role of a multimodal approach combining LUS, PCT, and clinical scores in reducing antibiotic prescribing showed that the approach demonstrated high implementation feasibility and safety in emergency department applications [35]. Incorporation of quantitative CT metrics into CURB-65 or PSI scores significantly improves the ability to predict critically ill patients [36]. Imaging histology, by extracting image features and combining them with artificial intelligence algorithms, enables automatic classification and prognostic prediction of severe pneumonia to support clinical decision making [6].

A notable limitation stems from the inconsistency and variability of definitions of pneumonia severity in the literature. For example, the PIDS/IDSA (Pediatric Infectious Diseases Society of America/Infectious Diseases Society of America) guidelines for pneumonia in children, although modified from adult criteria, have not been formally validated in children. This lack of standardization complicates effective risk stratification and resource allocation for patients with pneumonia [37]. In the adult population, the performance of existing severity scores (e.g., CURB-65 and CRB-65) in predicting mortality is considered suboptimal. Studies have shown the poor predictive ability of these scores, especially in critically ill patients admitted to the intensive care unit (ICU) for pneumonia [38]. A prospective cohort study showed that, despite their long history, established severity scoring systems such as the Simplified Acute Physiology Score 3 (SAPS 3) also performed poorly in accurately predicting outcomes, prompting the development of novel pneumonia-specific scores aimed at improving patient stratification [38]. Another limitation relates to the impact of host comorbidities on pneumonia severity and outcome. Factors such as age, existing chronic diseases (e.g., COPD, obesity, and renal insufficiency), and acute organ dysfunction may differ significantly between patients and affect mortality. These variables complicate the clinical picture, as certain comorbidities may not directly correlate with severity assessments derived from standardized scoring systems [39] [40]. In addition, emerging research on the impact of advanced imaging technologies (e.g., CT) suggests that there are potential avenues for assessing pneumonia severity based on the extent of identified lung lesions. This technique may enhance the prediction of respiratory failure and complications associated with COVID-19 pneumonia, e.g. [41]. However, such imaging methods require further validation to establish standardized criteria, especially given the dynamic and evolving nature of pneumonia assessment due to epidemics [40]. In summary, the assessment of severity

of severe pneumonia is hampered by inconsistent scoring criteria, the poor performance of existing models in critically ill populations, the need to consider the role of co-morbid conditions, and the evolving utility of imaging technologies. Addressing these limitations is critical to enhance clinical decision making, improve patient prognosis, and potentially guide resource allocation in healthcare settings.

5. The Role of Artificial Intelligence and Big Data in Assessment

5.1. Application of Machine Learning Models

Deep learning techniques, especially Convolutional Neural Network (CNN), have been applied to the classification of pneumonia as well as the assessment of the severity of the infection. By combining the dual methods of pneumonia classification and infection region segmentation, the CNN model is able to effectively improve the accuracy and efficiency of the detection of pneumonia. This method not only can quickly identify the presence of pneumonia, but also assess the severity of the disease by analyzing the size and distribution of the infected region [42]. Based on the synthesis of laboratory test results and clinical information, eXtreme Gradient Boosting (XGBoost), Categorical Boosting (CatBoost), and Light Gradient Boosting Machine (LGBM) and other integrated models for predicting the risk of death in patients with pneumonia [43]. These models enable more accurate identification of high-risk patients by fusing multiple biomarkers with clinical parameters.

5.2. Integration and Analysis of Multi-Omics Data

By integrating genomics, proteomics and metabolomics data, we reveal the pathogenesis of severe pneumonia and provide a scientific basis for individualized treatment. Jieqiong Li [44] *et al.* revealed overactive inflammatory responses, immunosuppression and lipid metabolism disorders in patients with severe community-acquired pneumonia through proteomics and metabolomics analyses. The MASS cohort constructed by Zhejiang University in conjunction with several hospitals revealed the dynamic changes of the lung and gut microbiomes and their association with severe pneumonia and host susceptibility through the integration of in-depth macrogenomics, transcriptomics and clinical data [45].

6. Directions for Future Research

6.1. Exploration of Novel Biomarkers

Future studies should aim to discover biomarkers with higher specificity and sensitivity to improve the accuracy of early diagnosis of severe pneumonia. Soluble Triggering Receptor Expressed on Myeloid Cells-1 (sTREM-1) is a member of the immunoglobulin superfamily, and its expression level is up-regulated in neutrophils, macrophages, and monocytes, and sTREM-1 levels are significantly increased in patients with severe pneumonia. levels are significantly elevated in pa-

tients with severe pneumonia and show a strong correlation with the degree of inflammation and the severity of the disease [46]. The expression level of Fibroblast Growth Factor-21 (FGF-21), a metabolic regulator, showed a strong correlation with the severity of severe pneumonia and could be used as an early predictor of poor prognosis [47]. Serum soluble CD14-ST (Presepsin) is a glycoprotein released during the inflammatory response, and its concentration shows a strong correlation with the severity of severe pneumonia, and therefore can be used as a valid biomarker [48]. The newly discovered biomarkers provide new research directions for the early diagnosis of severe pneumonia and the development of precise treatment strategies. However, these novel biomarkers face challenges such as high detection costs and complex technology in clinical applications. In the future, we need to develop more efficient and low-cost detection methods and validate their clinical value through multicenter studies.

6.2. Deep Integration of Imaging with Artificial Intelligence (AI)

Further optimization of imaging histology algorithms and development of intelligent diagnostic tools suitable for clinical use are important directions for future research. A high-precision CNN model has been successfully applied to pneumonia detection in chest X-ray images with an accuracy of up to 97.23%, and the interpretability of the model has been improved by integrating gradient techniques [49]. The PneumoAI system significantly improves the accuracy of pneumonia detection by Recent Advances in the Assessment Methods and Indicators for the Severity of Severe Pneumonia. The application of AI in the diagnosis of severe pneumonia still faces challenges, such as the limited generalization ability of AI tools, and the diversity and quality of datasets have a large impact on the performance of AI models. Therefore, there is a need to validate the performance of AI tools on large-scale benchmark datasets to improve their stability and reliability.

Assessing the severity of severe pneumonia faces several key challenges, particularly in the context of pneumonia caused by SARS-CoV-2 (COVID-19). Traditional assessment methods rely heavily on qualitative assessments by medical professionals (e.g., radiologists), which may introduce subjectivity and variability in interpretation. These qualitative methods may limit the ability to accurately quantify lung involvement and often rely on standardized scoring systems that may not adequately capture subtle differences in disease presentation. For example, semi-quantitative scoring systems are often unable to distinguish between [50] in a single region. Another significant limitation stems from the complex interplay between the various clinical and imaging factors that influence the severity of pneumonia. Clinical assessment often involves subjective judgment and can be time-consuming, with experts assessing each patient for up to 20 minutes. This complexity may impede timely therapeutic decision making at a critical time in patient care [51]. In addition, traditional scoring methods rely heavily on visual judgment, may be influenced by the radiologist's experience, and are prone to human error, which can prolong the decision-making process and potentially compro-

mise patient outcomes. AI-based methods effectively address these limitations by providing automated quantitative analysis of chest CT scans, allowing for a more objective assessment of pneumonia severity. AI algorithms are able to rapidly segment lung images and quantify specific features, such as opacity volumes and lesion distributions, resulting in a more accurate measure of lung involvement [52]. For example, AI-assisted quantification has shown comparable or even superior performance in predicting key outcomes compared to measurements assessed by radiologists. In one study, the final model integrating clinical and imaging parameters demonstrated high accuracy (83.9%), highlighting the potential of AI to improve diagnostic accuracy [51]. In addition, AI enhances predictive modeling by capturing large amounts of data that may be overlooked by traditional methods. Deep learning techniques, such as convolutional neural networks, have demonstrated the ability to generate interpretable outputs that summarize disease characteristics. This includes identifying disease-specific features that correlate with outcomes, such as increased length of stay and ICU admissions as a function of vacuolar opacity score [52] [53]. Such comprehensive data utilization enables AI systems to provide evidence-based prognostic information that can be used to adjust treatment plans, ultimately enabling better resource allocation in healthcare settings during surges in pneumonia cases. Additionally, AI facilitates faster, more reliable analysis, streamlining workflow in environments where imaging needs are overwhelming, such as during the COVID-19 pandemic. The ability to rapidly assess large amounts of data minimizes delays in patient care, which is critical when rapid interventions can alter the course of the disease [51] [54]. In summary, the integration of AI in assessing pneumonia severity mitigates traditional diagnostic challenges associated with subjective assessments, time delays, and inter-clinician variability. By providing deep learning-driven quantitative metrics, AI enhances the reliability and efficiency of pneumonia management, ensuring timely and effective interventions that significantly improve patient outcomes.

6.3. Individualized Assessment and Development of Treatment Strategies

Individualized assessment and treatment strategies based on multimodal data and AI models are key to improving the prognosis of severe pneumonia. The CarpeDiem model, based on ICU time-series data, is effective in predicting the progression and prognosis of patients with severe pneumonia [55]. AI models based on multimodal data show significant potential for classification of inflammatory subtypes and prognosis prediction in patients with severe pneumonia [56]. AI models can recommend the most appropriate antibiotic regimen by analyzing the pathogen characteristics and drug susceptibility of patients [57]. In addition, AI technology can be used for drug development and screening to identify potential antimicrobial peptides or antiviral drugs, providing new options for the treatment of severe pneumonia [58].

7. Conclusion

Methods of assessing the severity of severe pneumonia are evolving from traditional clinical indicators to multidimensional and intelligent. The use of emerging biomarkers, imaging technologies, and artificial intelligence provides new ideas for early identification and precise treatment strategies for severe pneumonia. Future research should focus on addressing the limitations of existing assessment methods, exploring novel biomarkers in depth, promoting the deep integration of imaging and AI, and developing individualized assessment and treatment strategies to further enhance the clinical management of severe pneumonia and improve patient prognosis.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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