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Artificial intelligence in the diagnosis and prognosis of pediatric bacterial pneumonia: current advances and challenges

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Purpose of review

The clinical presentation of pediatric bacterial pneumonia often overlaps with that of other respiratory conditions, posing considerable diagnostic challenges. This review evaluates the potential of artificial intelligence to improve diagnostic accuracy and prognostic evaluation for this disease.

Recent findings

Artificial intelligence driven diagnostic tools for pediatric bacterial pneumonia have now been validated in several studies. Clinically, these systems can rapidly process chest imaging, synthesize heterogeneous patient data, and alert physicians to early signs of severe pneumonia. Beyond immediate diagnostics, they also show emerging utility in uncovering biomarkers relevant to disease prognosis and management.

Summary

In clinical practice, artificial intelligence driven decision support is emerging as a valuable tool for the early diagnosis of pediatric bacterial pneumonia. As high-quality, multicenter datasets continue to grow and model interpretability improves, artificial intelligence is expected to become increasingly important in managing pediatric bacterial pneumonia.

Keywords

artificial intelligence, bacterial pneumonia, medical imaging, pediatrics

INTRODUCTION

Globally, pneumonia is a leading cause of hospitalization and mortality in children under 5 years of age [1]. This condition is most often caused by bacterial or viral pathogens. These infections require different treatments: antibiotics for bacterial cases and supportive care for viral ones [2▪▪]. However, accurately identifying the cause of community-acquired pneumonia remains clinically difficult. Many common diagnostic markers, such as consolidation on chest X-rays (CXRs) or elevated inflammatory markers, cannot reliably distinguish between viral and bacterial origins [3–5]. Microbiological culture of respiratory specimens is the traditional gold standard for diagnosis, but it has limited sensitivity, difficulty in obtaining quality specimens, and long processing times [6].

Machine learning, a core domain of artificial intelligence, allows computational models to learn from data, conduct statistical analysis, and produce automated decisions. Convolutional neural network (CNN) is a specialized form of machine learning that draws inspiration from neural networks. It processes information through multiple layers to identify complex patterns [7,8]. In healthcare, artificial intelligence assists in tasks like detecting rare diseases and predicting infectious disease outbreaks with public health relevance [9]. For pediatric bacterial pneumonia, artificial intelligence has shown strong results in enhancing medical imaging analysis and creating predictive models [10,11]. This review explores the use of artificial intelligence in diagnosing and predicting the disease, focusing on pathogen identification, severity assessment, and biomarker discovery (Fig. 1).

AUTOMATED DIAGNOSIS FROM MEDICAL IMAGING

Pneumonia represents a significant contributor to the pediatric disease burden, associated with considerable morbidity and mortality. Challenges in

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KEY POINTS

- Machine learning models based on medical imaging can extract subtle textures, densities, and distribution variations from chest X-rays or CT scans that are imperceptible to the human eye, enabling high-precision classification and accurate diagnosis of bacterial pneumonia.
- Multimodal machine learning models integrate imaging data with clinical information, effectively enhancing the feasibility of precision medicine and providing clinicians with objective decision support for early identification of pediatric patients with severe bacterial pneumonia.
- By integrating multidimensional data such as high throughput proteomics, metabolomics, and lipidomics, machine learning algorithms can identify diagnostic and prognostic biomarker profiles that are challenging to detect using conventional methods.

identifying causative pathogens often lead to indiscriminate antibiotic use, which in turn accelerates the spread of antimicrobial resistance [12]. Consequently, early and accurate pathogen detection, particularly distinguishing between bacterial and viral pneumonias, is crucial for improving clinical outcomes in children. Chest radiography remains the primary imaging modality for detecting pediatric pneumonia [13]. However, substantial overlap in imaging manifestations across different pneumonia types complicates differentiation using conventional methods [14]. Artificial intelligence can perform classifications that are difficult for human experts to perform. In particular, the development of CNN layers has significantly improved the ability to classify images and detect objects in images [15]. These are multiple processing layers to which image analysis filters, or convolutions, are applied. The abstracted representation of images within each layer is constructed by systematically convolving multiple filters across the image, producing a feature map that is used as input to the following layer. This architecture makes it possible to process images in the form of pixels as input and to give the desired classification as output [16].

To address the diagnostic challenge caused by overlapping imaging features of bacterial and viral pneumonia in children, ML models can be trained on large-scale pediatric CXR datasets. For example, the Guangzhou Pediatric Pneumonia dataset, developed by Kermany *et al.* [16], is a publicly available pediatric CXR collection. It contains 5856 orthotopic radiographs of children between 1 and 5 years old. These models learn to automatically identify subtle discriminative imaging patterns and have successfully achieved multiclass classification into normal, viral, and bacterial categories [17,18,19▪]. Beyond lesion detection, machine learning applications now support treatment decisions. For instance, a study has used low-dose chest CT images to develop machine learning based radiomics models. The model initially extracts hundreds of subtle radiomic features from low-dose chest CT images, which are difficult to quantify by visual inspection. Following feature dimensionality reduction, high-dimensional features are further refined to select those most relevant to the pathogenic etiology. Finally, a predictive classifier is constructed based on these selected features, that distinguish among Gram-positive, Gram-negative, and atypical bacterial pathogens. This capability offers an objective reference to guide empirical antibiotic selection in pediatric bacterial pneumonia [20,21].

Currently, electronic clinical decision support tools serve as a means to align patient care with

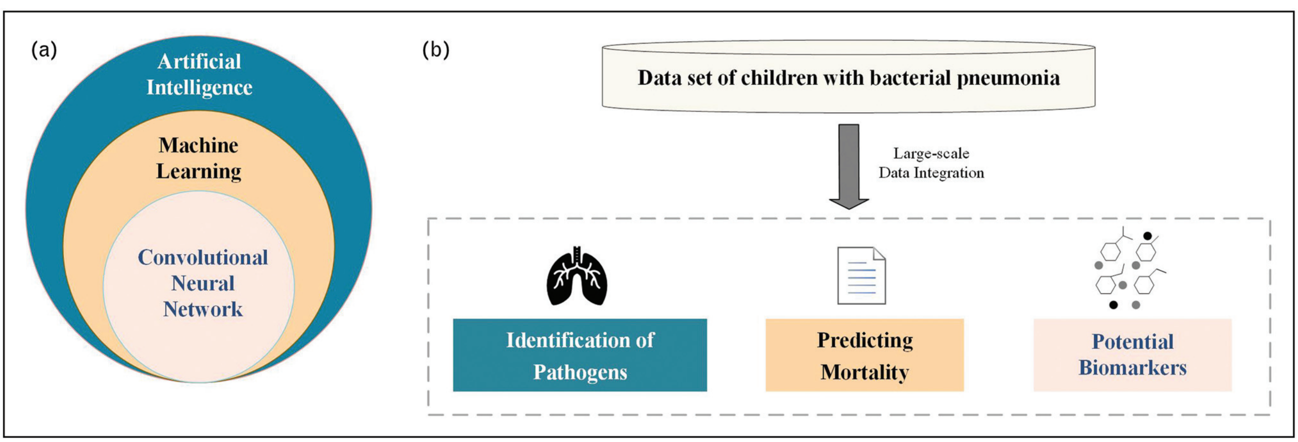

FIGURE 1. (a) Interrelationships of artificial intelligence, machine learning, and convolutional neural networks. (b) AI applications in diagnosing and predicting pediatric bacterial pneumonia.

guideline recommendations [22,23]. However, in pediatric pneumonia, their application faces limitations in incorporating imaging studies such as chest radiographs into electronic algorithms. Natural language processing (NLP) is a class of machine learning which uses rule-based algorithms to convert unstructured text into encoded data. In a retrospective study involving 829 751 imaging cases from six hospitals, Nancy Rixe *et al.* [24] employed NLP tools to enable rapid interpretation of chest radiograph reports and integrate coded results into electronic clinical decision support systems. Their model demonstrated high sensitivity (93.5%) and specificity (98.8%), improving both the efficiency of pneumonia identification and the capacity for epidemiological surveillance [24,25].

In recent years, lung ultrasonography (LUS) has advanced rapidly and is now widely used in the evaluation of pulmonary diseases in neonates and children [26]. Compared with CXRs, LUS offers several advantages that are particularly beneficial for the pediatric population: it involves no ionizing radiation, is relatively low-cost, is portable and accessible in various settings, and can be performed immediately as a bedside examination [27]. LUS has demonstrated high sensitivity and negative predictive value for pneumonia. It enables quantification of lung disease severity and outcomes [28▪], helps differentiate between viral and bacterial pneumonia, and shows potential in reducing antibiotic misuse [27,29]. Reinforcement learning is a subset of ML that facilitates the acquisition and interpretation of ultrasound images [30]. In cardiac ultrasound, for instance, deep learning techniques assist in guiding standard view acquisition, enhancing image quality, and automating assessments such as left ventricular ejection fraction estimation [31]. Moreover, artificial intelligence has shown high sensitivity in aiding LUS-based detection of pneumothorax [32]. Despite this promise, research on artificial intelligence assisted lung ultrasound for diagnosing bacterial pneumonia in children remains limited.

EARLY PREDICTION OF SEVERE PNEUMONIA WITH MACHINE LEARNING

Pneumonia remains a major cause of childhood mortality worldwide. Therefore, early identification of high-risk patients is crucial to improving clinical outcomes [33]. Machine learning technologies help build accurate predictive models by integrating multisource data, thereby offering personalized risk assessment. For example, prognostic models using inflammatory markers and cell counts from routine blood tests enable early risk stratification for severe pneumonia in children [34–36]. These data-driven methods can reveal complex, nonlinear relationships among clinical variables, offering clinicians objective decision support. In ICUs, machine learning models have been applied to dynamically assess mortality risk by analyzing admission vital signs, laboratory results, and complications. Such models assist in rational resource allocation and support the design of individualized treatment plans [37]. At the same time, researchers are developing generalizable risk assessment tools to address global public health needs. One multinational study created and validated a simple tool to identify the risk of in-hospital pneumonia mortality in children aged 2–59 months. By incorporating easily accessible variables such as age, nutritional status, and clinical signs, this tool shows strong potential for use in resource-limited settings [38].

INTEGRATED DIAGNOSIS USING MULTIMODAL DATA

Multimodal machine learning models demonstrate considerable promise in pediatric bacterial pneumonia diagnosis, pathogen identification, and prognosis prediction. By integrating imaging data with clinical information from electronic health records and laboratory biomarkers, these models significantly advance the feasibility of precision medicine in this domain [39–41]. A recent cohort study developed a predictive model for severe community-acquired pneumonia in children by integrating artificial intelligence derived chest CT parameters, including consolidation extent and ground-glass opacity features, with clinically adjusted electronic health record data such as age, white blood cell count, neutrophil and lymphocyte counts, creatinine levels, and the presence of wheezing. Radiomics enables quantitative evaluation of pulmonary lesion severity, thereby compensating for the limitations of relying solely on clinical indicators or subjective imaging interpretation. This approach enhances the objectivity of diagnosis and the capacity for early clinical warning [42▪▪].

ARTIFICIAL INTELLIGENCE DRIVEN DISCOVERY OF POTENTIAL BIOMARKERS

Biomarkers are quantifiable indicators of biological processes, pathogenic states, or therapeutic responses. They provide valuable tools for the early identification of severe pneumonia and for distinguishing between viral and bacterial causes [43]. Furthermore, using predictive or monitoring biomarkers can significantly improve treatment outcomes [44]. Conventional assays like ELISA and PCR are typically limited to detecting one or a few predefined targets, such as specific proteins or genes. This targeted approach makes it difficult to identify novel biomarker combinations or those involving complex multidimensional interactions [45,46]. In contrast, artificial intelligence algorithms can integrate multiomics data to uncover new diagnostic and prognostic biomarkers [47].

Artificial intelligence enhanced multiomics analyses show considerable promise for etiological differentiation. Research indicates that integrating proteomics, metabolomics, and lipidomics data can effectively distinguish bacterial from viral pneumonia [48,49▪]. In pediatric patients, certain blood protein signatures have proven reliable for identifying bacterial infections. These markers, which include HP, LCN2, and S100A9, are associated with neutrophil degranulation [50]. Computational biology methods also contribute to this field by enabling the design of optimized antimicrobial peptides. Using in silico site-directed mutagenesis, researchers can create novel pathways for developing diagnostic markers [51].

In prognosis prediction and critical illness identification, artificial intelligence technologies also show considerable promise. Zhongshu Kuang *et al.* [52] analyzed the proteomic and metabolomic data of patients with pneumonia at the time of admission, and found that in the severe pneumonia group, the levels of sphingosine-1-phosphate (S1P) and apolipoproteins (APOC1 and APOA2) were downregulated, while the level of S100P was significantly upregulated. This study may provide a possibility for elucidating the complexity of pneumonia severity [52]. Furthermore, Clarissa Valim *et al.* [53] analyzed the proteomes of 900 children admitted with pneumonia, aged 2–59 months. Their study identified a limited set of protein combinations that could accurately predict which patients would later experience clinical deterioration [53]. More innovative studies developed nanosensors that respond to host protease activity and used machine learning algorithms to interpret the urine signals generated. They found significant differences in urine reporter gene concentrations between mice with bacterial and viral pneumonia. Three (BV13, BV19, BV20) were significantly enriched in viral mice, while the other two (BV03 and BV04) were enriched in bacterial mice, demonstrating the great potential of non-invasive diagnostic techniques [54].

CHALLENGES AND FUTURE DIRECTIONS

While machine learning techniques show significant potential for diagnosing and predicting pediatric bacterial pneumonia, their widespread clinical use faces several limitations. The “black box” nature of many algorithms, especially in deep learning, raises concerns about interpretability and undermines clinical trust [55]. To address this, researchers have developed methods such as Shapley Additive exPlanations (SHAP). These tools quantify how individual variables influence predictions, which clarifies model mechanisms and improves transparency [56]. Another major challenge is overfitting, where models perform well on training data but fail to generalize to external validation cohorts [57]. Additionally, building robust models depends heavily on both the quality and quantity of available data. This process demands substantial domain expertise and computational resources. Importantly, incomplete or biased datasets can severely limit algorithmic performance [58].

Future research in machine learning for pediatric bacterial pneumonia should focus on three key directions. First, researchers should leverage large-scale, multicenter, and real-world datasets to reduce overfitting and improve model generalizability. Second, integrating multimodal data can enhance predictive performance. Such data may include genomic, phenotypic, clinical, and epidemiological information. Finally, closer collaboration between technology developers and pediatricians is essential. This will help ensure that model outputs are interpretable and actionable in clinical workflows, thereby directly supporting diagnostic and treatment decisions.

CONCLUSION

This review explores the application of artificial intelligence in the early diagnosis and prediction of pediatric bacterial pneumonia. It specifically covers automated diagnosis, predictive modeling, and biomarker discovery. These technologies help clinicians utilize large-scale, multisource data for the early detection of this disease. Furthermore, artificial intelligence supports the early identification of severe cases in clinical practice, which may lead to better patient outcomes. However, several key challenges remain. These include data heterogeneity, data quality limitations, and the black box nature of machine learning. Addressing these issues requires collaborative and multidisciplinary approaches. As high-quality, multicenter datasets continue to grow and model interpretability improves, artificial intelligence is expected to become increasingly important in managing pediatric bacterial pneumonia.

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Conflicts of interest

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REFERENCES AND RECOMMENDED READING

Papers of particular interest, published within the annual period of review, have been highlighted as:
■ of special interest
■■ of outstanding interest

1. GBD 2019 Diseases and Injuries Collaborators. Global burden of 369 diseases and injuries in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study. Lancet 2020; 396: 1204–1222.
2. ■■ Rickard D, Kabir MA, Homaira N. Machine learning-based approaches for distinguishing viral and bacterial pneumonia in paediatrics: a scoping review. Comput Methods Programs Biomed 2025; 268:108802.

This scoping review summarizes the evidence on ML techniques for classifying viral and bacterial pneumonia using CXR images in pediatric patients.

3. Lyon E, Olarte L. Community-acquired bacterial pneumonia in children: an update on antibiotic duration and immunization strategies. Curr Opin Pediatr 2024; 36:144–149.
4. Arnold SR, Jain S, Dansie D, *et al.* Association of radiology findings with etiology of community acquired pneumonia among children. J Pediatr 2023; 261:113333.
5. Wrotek A, Robakiewicz J, Pawlik K, *et al.* The etiology of community-acquired pneumonia correlates with serum inflammatory markers in children. J Clin Med 2022; 11:5506.
6. Shao J, Ma J, Yu Y, *et al.* A multimodal integration pipeline for accurate diagnosis, pathogen identification, and prognosis prediction of pulmonary infections. The Innovation 2024; 5:100648.
7. Collins GS, Moons KGM, Dhiman P, *et al.* TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods. BMJ 2024; 385:e078378.
8. Janiesch C, Zschech P, Heinrich K. Machine learning and deep learning. Electron Mark 2021; 31:685–695.
9. Haug CJ, Drazen JM. Artificial intelligence and machine learning in clinical medicine, 2023. N Engl J Med 2023; 388:1201–1208.
10. Aa T, Rc R. Artificial intelligence, machine learning and deep learning: potential resources for the infection clinician. J Infect 2023; 87:287–294.
11. Yen C-T, Tsao C-Y. Lightweight convolutional neural network for chest X-ray images classification. Sci Rep 2024; 14:29759.
12. Antimicrobial Resistance Collaborators. Global burden of bacterial antimicrobial resistance in 2019: a systematic analysis. Lancet 2022; 399:629–655.
13. Salvi M, Bosco M, Molinaro L, *et al.* A hybrid deep learning approach for gland segmentation in prostate histopathological images. Artif Intell Med 2021; 115: 102076.
14. Rotem-Grunbaum B, Scheuerman O, Tamary O, *et al.* Pediatric chest radiograph interpretation in a real-life setting. Eur J Pediatr 2024; 183: 4435–4444.
15. Mahootiha M, Tak D, Ye Z, *et al.* Multimodal deep learning improves recurrence risk prediction in pediatric low-grade gliomas. Neuro Oncol 2025; 27: 277–290.
16. Kermany DS, Goldbaum M, Cai W, *et al.* Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell 2018; 172: 1122–1131. e9.
17. Yazdani E, Neizehbaz A, Karamzade-Ziarati N, *et al.* Explainable artificial intelligence for pneumonia classification: clinical insights into deformable prototypical part network in pediatric chest x-ray images. J Med Imaging Radiat Sci 2025; 56:102023.
18. Morcos G, Yi PH, Jeudy J. Applying artificial intelligence to pediatric chest imaging: reliability of leveraging adult-based artificial intelligence models. J Am Coll Radiol 2023; 20:742–747.
19. ■ Nillmani, Jain P, Sharma N, *et al.* Four types of multiclass frameworks for pneumonia classification and its validation in X-ray scans using seven types of deep learning artificial intelligence models. Diagnostics 2022; 12:652.

This study employs seven deep-learning models to classify pneumonia types from CXRs, achieving high accuracy (up to 99.84%) in distinguishing COVID-19 from viral, bacterial, tubercular pneumonia, and normal cases, enabling fast, cost-effective diagnosis.

20. Zhang M, Yu S, Yin X, *et al.* An AI-based auxiliary empirical antibiotic therapy model for children with bacterial pneumonia using low-dose chest CT images. Jpn J Radiol 2021; 39:973–983.
21. Yang T, Zhang L, Sun S, *et al.* Identifying severe community-acquired pneumonia using radiomics and clinical data: a machine learning approach. Sci Rep 2024; 14:21884.
22. Karwa A, Patell R, Parthasarathy G, *et al.* Development of an automated algorithm to generate guideline-based recommendations for follow-up colonoscopy. Clin Gastroenterol Hepatol 2020; 18:2038–2045. e1.
23. Hou JK, Imler TD, Imperiale TF. Current and future applications of natural language processing in the field of digestive diseases. Clin Gastroenterol Hepatol 2014; 12:1257–1261.
24. Rixe N, Frisch A, Wang Z, *et al.* The development of a novel natural language processing tool to identify pediatric chest radiograph reports with pneumonia. Front Digit Health 2023; 5:1104604.
25. Abdulahi AT, Ogundokun RO, Adenike AR, *et al.* PulmoNet: a novel deep learning based pulmonary diseases detection model. BMC Med Imaging 2024; 51.
26. Shi C, Xu X, Xu Y. Systematic review and meta-analysis of the accuracy of lung ultrasound and chest radiography in diagnosing community acquired pneumonia in children. Pediatr Pulmonol 2024; 59:3130–3147.
27. Buonsenso D, Musolino A, Ferro V, *et al.* Role of lung ultrasound for the etiological diagnosis of acute lower respiratory tract infection (ALRTI) in children: a prospective study. J Ultrasound 2022; 25:185–197.
28. ■ Xie W, Ruan J, Jiang Q, *et al.* Distinguishing types and severity of pediatric pneumonia using modified lung ultrasound score. Front Pediatr 2024; 12: 1411365.

The modified lung ultrasound score, coupled with ultrasound signs of large-area lung consolidation, had reference significance for the differential diagnosis of Mycoplasma pneumonia and viral pneumonia in children and can be a preliminary assessment of the severity of viral pneumonia or mycoplasma pneumonia in children.

29. Malla D, Rathi V, Gomber S, *et al.* Can lung ultrasound differentiate between bacterial and viral pneumonia in children? J Clin Ultrasound 2021; 49:91–100.
30. Boccatonda A. Emergency ultrasound: is it time for artificial intelligence? J Clin Med 2022; 11:3823.
31. Narang A, Bae R, Hong H, *et al.* Utility of a deep-learning algorithm to guide novices to acquire echocardiograms for limited diagnostic use. JAMA Cardiol 2021; 6:624–632.
32. Montgomery S, Li F, Funk C, *et al.* Detection of pneumothorax on ultrasound using artificial intelligence. J Trauma Acute Care Surg 2023; 94:379–384.
33. Cao S, Liu L, Yang L, *et al.* Assessing severe pneumonia risk in children via clinical prognostic model based on laboratory markers. Int Immunopharmacol 2025; 151:114317.
34. Liu Y, Wu Q, Zhou L, *et al.* Constructing a diagnostic prediction model to estimate the severe respiratory syncytial virus pneumonia in children based on machine learning. Shock 2025; 63:533–540.
35. Ye Y, Gao Z, Zhang Z, *et al.* A machine learning model for predicting severe mycoplasma pneumoniae pneumonia in school-aged children. BMC Infect Dis 2025; 25:570.
36. Pourakbari B, Mamishi S, Valian SK, *et al.* Predicting COVID-19 severity in pediatric patients using machine learning: a comparative analysis of algorithms and ensemble methods. Sci Rep 2025; 15:29118.
37. Lin S, Wu J, Liu Y, *et al.* Machine learning models to evaluate mortality in pediatric patients with pneumonia in the intensive care unit. Pediatr Pulmonol 2024; 59:1256–1265.
38. Rees CA, Colbourn T, Hooli S, *et al.* Derivation and validation of a novel risk assessment tool to identify children aged 2-59 months at risk of hospitalised pneumonia-related mortality in 20 countries. BMJ Glob Health 2022; 7: e008143.
39. Zhang Q, Huang A, Shao L, *et al.* A machine learning framework for identifying influenza pneumonia from bacterial pneumonia for medical decision making. J Comput Sci 2022; 65:101871.
40. Song L, Zhan Y, Li L, *et al.* Differentiating bacterial and nonbacterial pneumonia on chest CT using multiplane features and clinical biomarkers. Acad Radiol 2025; 32:5596–5608.
41. Wen R, Xu P, Cai Y, *et al.* A deep learning model for the diagnosis and discrimination of gram-positive and gram-negative bacterial pneumonia for children using chest radiography images and clinical information. Infect Drug Resist 2023; 16:4083–4092.
42. ■■ He M, Yuan J, Liu A, *et al.* A cohort study of pediatric severe community-acquired pneumonia involving AI-based CT image parameters and electronic health record data. Infect Dis Ther 2025; 14:2131–2141.

This study demonstrates that artificial intelligence models integrating chest CT imaging features with clinical data can effectively predict respiratory failure in pediatric patients with severe community-acquired pneumonia, facilitating improved risk stratification.

43. Ding L, Jiang Y. Biomarkers associated with the diagnosis and prognosis of Mycoplasma pneumoniae pneumonia in children: a review. Front Cell Infect Microbiol 2025; 15:1552144.
44. Pletz MW, Jensen AV, Bahrs C, *et al.* Unmet needs in pneumonia research: a comprehensive approach by the CAPNETZ study group. Respir Res 2022; 23:239.
45. Ou FS, Michiels S, Shyr Y, *et al.* Biomarker discovery and validation: statistical considerations. J Thorac Oncol 2021; 16:537–545.
46. Pickens CI, Gao CA, Morales-Nebreda L, Wunderink RG. Microbiology of severe community-acquired pneumonia and the role of rapid molecular techniques. Semin Respir Crit Care Med 2024; 45:158–168.
47. Araújo R, Bento LFN, Fonseca TAH, *et al.* Infection biomarkers based on metabolomics. Metabolites 2022; 12:92.
48. Lydon E, Osborne CM, Wagner BD, *et al.* Proteomic profiling of the local and systemic immune response to pediatric respiratory viral infections. Msystems 2025; 10:e0133524.

49. Rischke S, Gurke R, Zielbauer A-S, *et al.* Proteomic, metabolomic and
■ lipidomic profiles in community acquired pneumonia for differentiating viral and bacterial infections. Sci Rep 2025; 15:1922.

This multiomics study identifies distinct plasma molecular signatures – including specific lipids, metabolites, and proteins – that differentiate viral from bacterial pneumonia, offering potential biomarkers for improved diagnosis and targeted treatment.

50. Gillette MA, Mani DR, Uschnig C, *et al.* Biomarkers to distinguish bacterial from viral pediatric clinical pneumonia in a malaria-endemic setting. Clin Infect Dis 2021; 73:e3939–e3948.
51. Bakare OO, Gokul A, Keyster M. Analytical studies of antimicrobial peptides as diagnostic biomarkers for the detection of bacterial and viral pneumonia. Bioengineering (Basel) 2022; 9:305.
52. Kuang Z, Li R, Lu S, *et al.* Uncovering host response in adults with severe community-acquired pneumonia: a proteomics and metabolomics perspective study. World J Emerg Med 2025; 16:248–255.
53. Valim C, Olatunji YA, Isa YS, *et al.* Seeking diagnostic and prognostic biomarkers for childhood bacterial pneumonia in sub-Saharan Africa: study protocol for an observational study. BMJ Open 2021; 11:e046590.
54. Anahtar M, Chan LW, Ko H, *et al.* Host protease activity classifies pneumonia etiology. Proc Natl Acad Sci U S A 2022; 119:e2121778119.
55. Giacobbe DR, Marelli C, Guastavino S, *et al.* Explainable and interpretable machine learning for antimicrobial stewardship: opportunities and challenges. Clin Ther 2024; 46:474–480.
56. Dickinson Q, Meyer JG. Positional SHAP (PoSHAP) for Interpretation of machine learning models trained from biological sequences. PLoS Comput Biol 2022; 18:e1009736.
57. Xu J, Li F, Leier A, *et al.* Comprehensive assessment of machine learning-based methods for predicting antimicrobial peptides. Brief Bioinform 2021; 22:bbab083.
58. Ali T, Ahmed S, Aslam M. Artificial intelligence for antimicrobial resistance prediction: challenges and opportunities towards practical implementation. Antibiot Basel Switz 2023; 12:523.