

Review

Artificial Intelligence in Neonatal Respiratory Care: Current Applications and Future Directions

Aikaterini Nikolaou , Maria Baltogianni, Niki Dermitzaki , Nikitas Chatzigiannis, Dimitra Savidou, Sevastianos Geitonas, Lida-Eleni Giaprou and Vasileios Giapros *

Neonatal Intensive Care Unit, School of Medicine, University of Ioannina, 45500 Ioannina, Greece; nikaikaterini@gmail.com (A.N.); mbalt@doctors.org.uk (M.B.); n.dermitzaki@uoi.gr (N.D.); nikihatzi@gmail.com (N.C.); dimitrasavidou@yahoo.com (D.S.); sevastianosgeitonas@gmail.com (S.G.); md07243@uoi.gr (L.-E.G.)

* Correspondence: vgiapros@uoi.gr

Abstract

Respiratory disorders remain a major cause of morbidity and mortality in neonatal intensive care units, particularly among preterm infants. Advances in physiological monitoring, medical imaging, and electronic health records have enabled the growing application of artificial intelligence in neonatal respiratory care. This narrative review summarizes current applications and emerging directions of artificial intelligence in the diagnosis, monitoring, and management of neonatal respiratory disorders. Machine learning and deep learning approaches have demonstrated promising performance in respiratory distress syndrome, bronchopulmonary dysplasia, apnea of prematurity, ventilatory management, and severe respiratory complications. By integrating multimodal clinical, physiological, and imaging data, these methods support earlier detection of respiratory deterioration and improved clinical decision-making. However, challenges related to data quality, generalizability, interpretability, and limited prospective validation continue to constrain widespread clinical implementation, highlighting the need for careful integration into neonatal care workflows.

Keywords: artificial intelligence (AI); neonatal intensive care unit (NICU); neonatal respiratory disorders; neonatal respiratory monitoring; respiratory distress syndrome (RDS); bronchopulmonary dysplasia (BPD); machine learning (ML); deep learning (DL); clinical decision support; mechanical ventilation



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1. Introduction

Respiratory disorders are among the most commonly addressed clinical problems in neonatal intensive care, particularly in preterm neonates. Clinical entities such as respiratory distress syndrome (RDS), bronchopulmonary dysplasia (BPD), apnea of prematurity, and respiratory failure are consistently identified in recent reviews as major clinical targets for artificial intelligence-based applications in the neonatal intensive care unit (NICU) setting [1–3]. Despite considerable advances in perinatal and neonatal medicine, timely diagnosis, accurate risk stratification, and individualized respiratory management continue to pose significant challenges, largely due to the complex pathophysiology of the immature lung and the pronounced heterogeneity of neonatal populations [1,3]. In clinical practice, even modest delays in recognizing respiratory deterioration or optimizing respiratory support may have a disproportionate impact on short- and long-term outcomes, underscoring the central role of respiratory monitoring and decision support in neonatal intensive care [2].

Conventional respiratory management in the NICU relies primarily on clinical examination, intermittent imaging, physiological monitoring, and clinician expertise. In daily NICU practice, the primary challenge is often not the lack of available respiratory data but the difficulty of integrating fragmented clinical, physiological, and imaging information into timely and coherent bedside decisions. Although these approaches have improved survival, several reviews highlight their limitations in supporting early risk prediction and individualized prognostication, which has contributed to growing interest in AI-based approaches [1,4,5]. Consequently, there has been growing interest in applying artificial intelligence (AI) to enhance diagnostic accuracy, support therapeutic decision-making, and facilitate the delivery of precision respiratory care in neonates.

AI encompasses a broad range of computational techniques that enable systems to learn from data and perform tasks traditionally requiring human intelligence. In the field of neonatology, the adoption of AI has been driven by the increasing availability of high-resolution physiological data, comprehensive electronic health records (EHRs), and advanced digital medical imaging. Recent systematic and narrative reviews have documented a rapid expansion of AI-based applications within NICUs, consistently identifying respiratory disorders as one of the most extensively studied and clinically relevant domains [1–3,5]. Within this context, AI should be viewed as a clinical augmentation tool designed to support, rather than replace, clinician judgment in the management of complex neonatal respiratory conditions.

Beyond disease-specific use cases, AI is increasingly conceptualized as a clinical decision support paradigm rather than a substitute for clinician expertise. Intelligent systems are designed to augment clinical judgment by synthesizing large volumes of heterogeneous data and translating them into actionable insights at the point of care, thereby supporting complex decision-making processes in high-acuity environments such as the NICU [6].

Recent narrative reviews emphasize that neonatal respiratory disorders represent one of the most extensively explored areas for AI applications in the NICU. This is attributed to the continuous availability of respiratory and physiological data, the clinical importance of respiratory support in neonatal care, and the potential for earlier identification of clinical deterioration [5]. Collectively, these characteristics position neonatal respiratory care as a model use case for the responsible and clinically integrated deployment of AI technologies. Accordingly, this narrative review focuses on the role of AI in the diagnosis, monitoring, and treatment of neonatal respiratory disorders, with particular emphasis on disease-specific applications and their clinical relevance.

A comprehensive literature search was conducted between September and mid-December 2025 using the electronic databases PubMed, Scopus, and Google Scholar, with the following search terms: (“artificial intelligence” OR “machine learning” OR “deep learning” OR “convolutional neural network”) AND (“neonate” OR “newborn” OR “neonatal intensive care”) AND (“respiratory distress syndrome” OR “respiratory monitoring” OR “lung imaging” OR “mechanical ventilation”). Reference lists of relevant articles were also manually screened to identify additional pertinent studies. Studies were considered eligible for inclusion if they met the following criteria: (i) human studies involving neonatal populations (≤ 28 days of life), including preterm neonates; (ii) investigations evaluating AI-based methodologies for respiratory diagnosis, prediction, monitoring, or therapeutic management; (iii) original research articles, clinical studies, and prospective or retrospective cohort studies, including validation studies; and (iv) publications written in English. Studies were excluded if they: (i) focused exclusively on adult populations or non-neonatal pediatric cohorts; (ii) addressed non-respiratory conditions not relevant to neonatal respiratory outcomes; (iii) consisted of animal studies, editorials, commentaries, or purely

theoretical works without clinical applicability; or (iv) lacked sufficient methodological detail or outcome data.

All retrieved records were initially screened at the title and abstract level to assess relevance. Subsequently, full-text articles were reviewed to determine eligibility for inclusion. Duplicate records were removed prior to screening. Any discrepancies during the selection process were resolved through discussion and consensus among the reviewers. As this is a narrative review, no formal assessment of study quality or risk of bias was performed; this has been acknowledged as a limitation. A total of 1188 articles were identified through database searching and 33 additional records were identified through other sources (total $n = 1221$), of which 42 were found to be relevant. A PRISMA-style flow diagram was used to illustrate the process of study identification, screening, eligibility assessment, and final inclusion (Figure 1). The final body of included studies was synthesized thematically, with emphasis on: (a) AI-based predictive models for neonatal respiratory distress; (b) machine learning (ML) and deep learning (DL) applications in respiratory monitoring and imaging; (c) comparative performance of AI architectures, including convolutional neural networks (CNNs); and (d) clinical applicability, scalability, and limitations of AI tools, with particular consideration of implementation in resource-limited neonatal care settings. Respiratory care was selected as the focus of this review because it represents a data-rich, clinically time-sensitive domain in which early decision support has the potential to meaningfully influence neonatal outcomes.

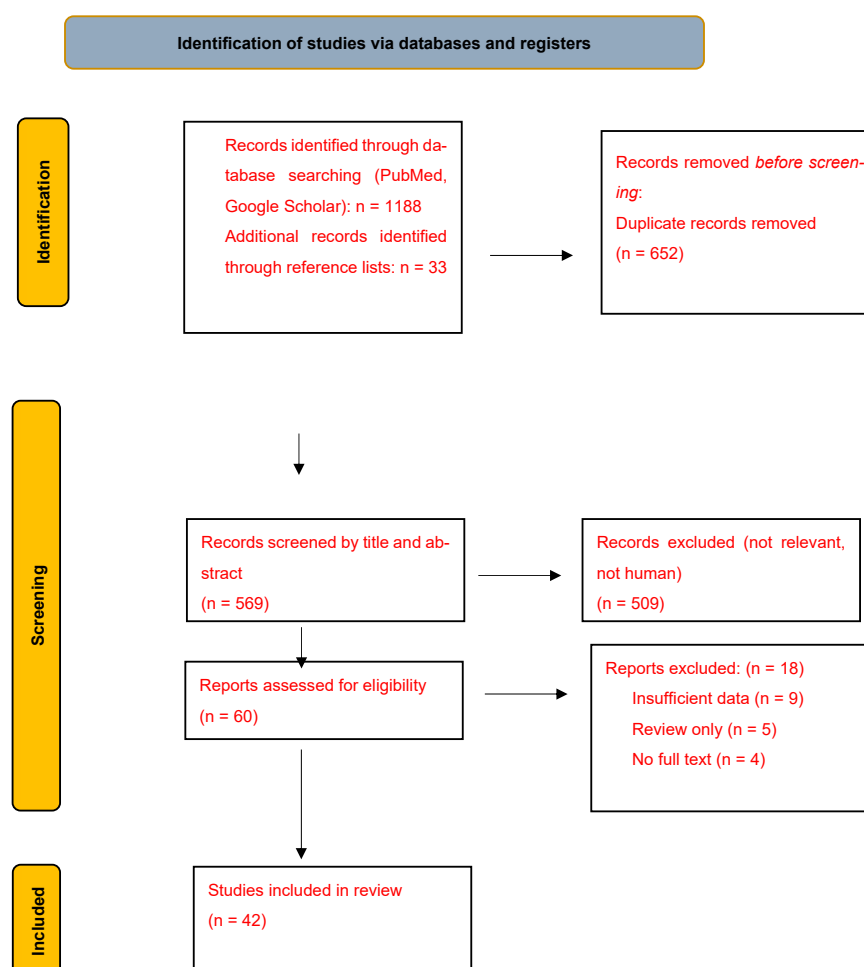


Figure 1. PRISMA flow diagram of search procedure.

2. Burden of Neonatal Respiratory Disease

Neonatal respiratory morbidity encompasses a heterogeneous group of clinical conditions commonly encountered in the NICU, particularly among preterm infants. RDS is among the most frequently included diagnostic categories in recent AI-based studies using neonatal chest radiographs and lung ultrasound data [7,8]. BPD is a key clinical outcome of interest in neonatal respiratory care and has been the focus of multiple ML-based prediction models, including large population-based studies [9–11].

In addition, apnea of prematurity and outcomes related to respiratory support, such as extubation readiness, are increasingly being investigated using ML approaches for detection and clinical decision support [12,13]. Collectively, these clinical challenges underscore the need for improved approaches to early detection, monitoring, and individualized respiratory management in neonatal care.

Evidence from large-scale reviews indicates that AI-based models are particularly well suited to address these challenges, as they can integrate large volumes of heterogeneous data and identify complex, non-linear relationships that are not readily apparent using traditional statistical methods [1,2,4].

3. Overview of AI Techniques in Neonatal Respiratory Medicine

3.1. Machine Learning (ML) and Deep Learning (DL)

ML encompasses a range of algorithms that learn patterns from data to perform prediction or classification tasks. In neonatal respiratory care, commonly used ML techniques include logistic regression, decision trees, random forests, and gradient boosting algorithms, as reported across systematic reviews and large-scale prediction studies [1,6,9,11]. These methods have been applied extensively to risk prediction, outcome forecasting, and phenotype classification, particularly for conditions such as BPD, respiratory deterioration, and oxygen or respiratory support requirements [1,5,9–11].

DL, a subset of ML, utilizes multilayer neural networks capable of learning hierarchical feature representations. DL models are especially effective for handling unstructured data, such as medical images and continuous physiological signals, which are commonly generated in the NICU environment [4,5,8]. CNNs, in particular, have demonstrated strong performance in the automated analysis of neonatal chest radiographs and lung ultrasound images for the detection of respiratory pathology, including RDS and other parenchymal lung diseases [7,8].

3.2. Data Sources for AI in Neonatal Respiratory Care

AI-based respiratory models in neonatology draw upon diverse and often multimodal data sources, including:

- Clinical and demographic variables, such as gestational age, birth weight, and antenatal exposures;
- Physiological monitoring data, including heart rate, respiratory rate, and oxygen saturation;
- Ventilator parameters, such as fraction of inspired oxygen (FiO₂), positive end-expiratory pressure (PEEP), and tidal volume;
- Medical imaging, including chest radiographs and lung ultrasound;
- Electronic health records.

Studies have consistently shown that multimodal AI models outperform single-modality approaches, particularly for predicting respiratory deterioration and long-term respiratory outcomes [1,4].

4. Rationale for AI Adoption in Neonatal Respiratory Care

4.1. Early Detection and Risk Stratification

One of the primary advantages of AI lies in its ability to identify subtle physiological and clinical patterns that precede overt respiratory deterioration [1,4–6]. ML models trained on early neonatal clinical and imaging data have demonstrated promising performance for early risk stratification and prediction of BPD supporting their potential role in augmenting clinical decision-making [9–11].

Similarly, DL-based image analysis has shown promise in the early identification of RDS severity from chest radiographs and lung ultrasound images, potentially guiding timely surfactant administration and ventilatory strategies [7,8]. However, predictive performance varies substantially across models and populations, and not all AI-based risk stratification tools demonstrate consistent robustness when applied outside the settings in which they were developed [1,6–8].

4.2. Continuous Monitoring and Real-Time Decision Support

AI-enabled monitoring systems extend beyond traditional threshold-based alarms by continuously analyzing high-frequency physiological data streams to identify complex temporal and multivariate patterns indicative of evolving respiratory instability [1,4–6]. Wearable, non-invasive, AI-driven technologies have further enhanced neonatal respiratory and cardiorespiratory monitoring by improving signal robustness, reducing motion-related artifacts, and facilitating continuous physiological assessment with minimal patient burden [1,4,5,14].

These advances provide the technological foundation for more proactive respiratory care in the neonatal intensive care unit by enabling earlier recognition of subtle physiological changes that may precede clinical deterioration.

4.3. Precision Medicine and Personalized Therapy

AI supports the transition toward precision neonatal respiratory care, in which therapeutic decisions are tailored to the individual infant's risk profile and physiological response [1,5,6,15]. Predictive models have been developed to support clinical decision-making related to respiratory management, including early prediction of RDS and BPD, prediction of the need for invasive mechanical ventilation, identification of failure of non-invasive respiratory support, and assessment of extubation readiness [13,16–20]. These approaches demonstrate promising predictive performance and highlight the potential of AI-based tools to support more individualized and proactive respiratory care in the neonatal intensive care unit.

5. Scope and Objectives of This Review

Given the rapid expansion and heterogeneity of AI research in neonatology, focused synthesis is required to clarify clinical applicability. This narrative review concentrates specifically on neonatal respiratory disorders, aiming to synthesize evidence on how AI contributes to:

- Respiratory monitoring and deterioration detection, including apnea and oxygen instability [4,12,14,18,19];
- Therapeutic decision-making, such as ventilator management and extubation readiness [5,6,13,18–20];
- Clinical integration, ethical considerations, and future research directions [1,5,6,21,22];
- Diagnosis, early prediction, and improved objectivity in the assessment of respiratory conditions, particularly RDS and BPD [7–11,15–17,23].

By organizing the literature according to disease-specific applications, this review aims to provide clinicians and researchers with a structured, clinically relevant overview of current capabilities, limitations, and future opportunities for AI in neonatal respiratory medicine.

6. AI in the Diagnosis and Management of Neonatal Respiratory Disorders

6.1. Respiratory Distress Syndrome (RDS)

6.1.1. Pathophysiological Background and Clinical Challenges

RDS remains one of the most common and severe respiratory conditions affecting preterm neonates, primarily resulting from surfactant deficiency and structural immaturity of the lung. Despite standardized diagnostic criteria based on clinical presentation, oxygen requirement, and radiographic findings, the early identification of disease severity and prediction of therapeutic needs remain challenging in routine clinical practice [2,3].

Conventional diagnostic approaches are limited by interobserver variability in imaging interpretation among clinicians, including radiologists and neonatologists [24], delayed recognition of worsening lung function, and an inability to accurately predict which infants will progress to severe respiratory failure or require invasive ventilation. These limitations have motivated the development of AI-based approaches that integrate clinical, physiological, and imaging data to improve early diagnosis and guide management decisions [1,3,5].

6.1.2. AI-Assisted Imaging for RDS Diagnosis

Medical imaging plays a central role in the diagnosis and assessment of RDS. Recent advances in DL have enabled the automated analysis of neonatal chest radiographs and lung ultrasound images with promising diagnostic performance. CNN-based models have been trained to classify chest radiographs into diagnostic categories including RDS. Studies have demonstrated that these models can achieve high diagnostic performance and substantial agreement with expert clinical assessments in image classification tasks [7,8].

In particular, Cho et al. developed a CNN-based framework for the automated classification of neonatal respiratory diseases, including RDS, from chest radiographs, reporting high diagnostic performance. Similarly, Fatima et al. demonstrated that DL algorithms could reliably classify neonatal lung ultrasound images and differentiate RDS from other patterns of neonatal lung disease [7,8].

DL models applied to lung ultrasound images have shown robust classification performance, supporting their potential role as rapid and reproducible tools for image-based decision support in the NICU [8].

6.1.3. Prediction of Disease Severity and Surfactant Requirement Using AI

Beyond diagnosis, AI has shown increasing promise in predicting the severity of RDS and guiding therapeutic interventions, particularly surfactant administration. ML models incorporating early clinical variables, ventilatory parameters, and, in some cases, imaging-derived features have been developed to identify infants at high risk for severe RDS requiring invasive mechanical ventilation or repeated surfactant dosing [1,3].

Early and accurate severity stratification is critical, as timely surfactant administration and appropriate escalation of respiratory support have been shown to influence both short- and long-term pulmonary outcomes. Recent large-scale ML studies conducted outside East Asia further support the robustness and generalizability of such approaches. In particular, a DL model trained on data from more than 13,000 neonates across 76 hospitals in the United States demonstrated strong performance in early prediction of RDS, illustrating the poten-

tial applicability of AI-based risk stratification across diverse healthcare systems [24]. In a multicenter prospective cohort study, Jang et al. developed and validated AI-driven prediction models for RDS severity in very low birth weight infants using perinatal and early postnatal clinical data. The models demonstrated robust predictive performance across participating centers, highlighting the feasibility and generalizability of AI-based early severity assessment shortly after birth, with direct implications for optimizing surfactant timing and individualized respiratory management strategies [16].

Collectively, these predictive tools enable earlier and more targeted therapeutic interventions, potentially reducing exposure to prolonged mechanical ventilation and associated lung injury. The integration of AI-driven risk stratification into clinical workflows has therefore been proposed as a means to support personalized respiratory management strategies in preterm infants, complementing clinician judgment and established treatment protocols [2,5].

6.2. Bronchopulmonary Dysplasia (BPD)

6.2.1. Clinical Significance and Need for Early Prediction

BPD is a chronic lung disease that predominantly affects extremely preterm infants who survive early respiratory failure. The condition is associated with prolonged respiratory support and significant long-term respiratory morbidity. Importantly, the clinical diagnosis of BPD is typically established several weeks after birth, which substantially limits opportunities for early preventive intervention during a critical window of lung development [9–11,15,17].

This diagnostic delay has driven extensive research into AI-based models capable of predicting BPD risk during the early neonatal period, when targeted preventive strategies and individualized respiratory management may be most effective [9–11,15,17]. Recent literature has increasingly recognized BPD as one of the most promising targets for AI-driven risk stratification in neonatal respiratory care [1,9,10,15].

6.2.2. Machine Learning Models for Early BPD Prediction

Multiple studies have demonstrated that ML algorithms can predict the subsequent development of BPD with moderate to high accuracy using data collected within the first days or weeks of life. More recently, large-scale models trained on multi-institutional real-world datasets have further strengthened this evidence base. In particular, a pre-trained clinical language model developed and validated using large neonatal datasets from multiple centers in the United States demonstrated robust performance in predicting several neonatal outcomes, including BPD and RDS, supporting the applicability of AI-based prediction beyond geographically restricted cohorts [25]. These models typically integrate gestational age, birth weight, oxygen exposure, ventilator settings, and early clinical course variables [1].

Recent systematic review and meta-analysis highlighted the promising performance of ML-based models compared with traditional regression approaches for BPD prediction, particularly when multimodal datasets were employed [11,12]. Importantly, extending the temporal scope of prediction even earlier, Verder et al. demonstrated that AI-based models could predict BPD at birth using perinatal variables alone, highlighting the feasibility of identifying high-risk infants before the onset of significant respiratory morbidity [17].

Building on this concept of very early risk stratification, Yoneda et al. developed a gradient boosting decision tree model using a nationwide Japanese neonatal database to predict death or BPD immediately after birth in very preterm and very low birth weight infants. Their model demonstrated strong discriminative performance using variables available

within the first hours of life, underscoring the potential of AI-based approaches to enable timely preventive respiratory strategies during a critical window of lung development [11].

Similarly, Zhang et al. developed ML-based risk prediction models for BPD in a large cohort of preterm infants, reporting good to excellent discriminative performance (with AUCs approaching 0.9 for the best-performing models) using routinely collected early clinical variables, further supporting the clinical utility of ML-based risk stratification across diverse neonatal populations [26]. Lei et al. likewise demonstrated that ensemble learning techniques could effectively stratify BPD risk in preterm infants, thereby supporting earlier clinical decision-making and individualized care planning [27].

In addition to individual predictive studies, a recent disease-focused narrative review by Jha et al. synthesized the growing body of evidence on the use of AI in BPD. The authors emphasized the potential of AI-based models to identify high-risk infants earlier than conventional diagnostic criteria, reinforcing the potential role of AI in enabling proactive respiratory management and lung-protective strategies during the early neonatal period [15]. Importantly, several other studies have likewise emphasized that AI-driven risk stratification can precede traditional diagnostic frameworks, creating opportunities for earlier intervention and personalized respiratory care pathways [9,11,17].

6.2.3. Integration of Imaging and Longitudinal Data

Recent advances have extended BPD prediction models beyond static clinical variables to incorporate imaging data and longitudinal physiological monitoring. DL approaches applied to chest radiographs have shown promise for predicting subsequent BPD development using imaging data collected during the early neonatal period [9,10,28].

In particular, CNN-based models trained on neonatal chest radiographs have demonstrated the ability to extract imaging features predictive of subsequent BPD development. Chou et al. developed a DL model using chest radiographs from preterm infants, reporting strong predictive performance for BPD and highlighting the potential of imaging-based AI approaches to identify high-risk infants early in the clinical course [28].

Furthermore, AI models leveraging continuous ventilator parameters and oxygenation data have demonstrated the feasibility of incorporating longitudinal ventilator parameters and oxygenation data to account for temporal trends rather than relying solely on single-time-point measurements [4,18]. As emphasized in recent reviews, including disease-focused syntheses of AI applications in BPD, the integration of multimodal imaging and longitudinal data aligns closely with the dynamic pathophysiology of neonatal lung disease and may substantially enhance the clinical utility and translational potential of AI-based prediction tools [5,9,10,15]. Moreover, variability in imaging protocols, data quality, and center-specific respiratory practices may affect model generalizability across different neonatal intensive care settings.

6.2.4. AI-Enabled Long-Term Management and Post-Discharge Respiratory Care

Building upon these in-hospital predictive and monitoring approaches, AI has begun to play an emerging role in the long-term management of infants with chronic neonatal lung disease following discharge from the NICU. AI-enabled conversational agents and chatbot-based platforms have been proposed as tools to support caregivers and healthcare professionals in managing home oxygen therapy, monitoring respiratory symptoms, and facilitating timely communication with clinical teams.

In a recent evaluation, Liu et al. assessed the use of AI chatbots in the management of chronic neonatal lung disease and home oxygen therapy, demonstrating the potential of such systems to improve caregiver education, adherence to respiratory care plans, and continuity of care after hospital discharge. These findings suggest that conversational AI

may complement traditional follow-up models and extend the reach of respiratory decision support beyond the NICU environment, particularly for infants with BPD and ongoing oxygen dependence [29].

6.3. Prediction of Severe Respiratory Complications

Beyond chronic lung disease, preterm and critically ill neonates are at risk for acute and potentially life-threatening respiratory complications associated with mechanical ventilation, including pulmonary hemorrhage and ventilator-associated pneumonia, for which early clinical recognition remains challenging.

Recent advances have demonstrated that AI-based models may support early risk stratification for severe respiratory complications. Aly et al. developed ML models to predict pulmonary hemorrhage in preterm infants using early clinical and perinatal variables and reported strong predictive performance, highlighting the potential of AI-driven approaches to identify high-risk infants prior to overt clinical deterioration [30]. Similar approaches have been applied to other acute respiratory risks, including early prediction of the need for mechanical ventilation and detection of hypoxia and apnea events using ML techniques [31,32].

In addition to predictive modeling, DL approaches have been applied to the early diagnosis of ventilator-associated pneumonia in mechanically ventilated neonates. Hsu et al. developed DL models demonstrating high diagnostic performance for identifying ventilator-associated pneumonia, suggesting that AI-assisted systems may support earlier recognition of this complication in the NICU [33].

Collectively, these emerging applications underscore the expanding role of AI in neonatal respiratory care, extending beyond chronic disease prediction to encompass early identification and risk stratification of acute ventilation-related complications, with potential relevance for clinical decision support [21,34].

6.4. Apnea of Prematurity and Respiratory Instability

Apnea of prematurity represents another clinically important respiratory condition characterized by recurrent pauses in breathing and associated oxygen desaturation. Conventional monitoring systems in the NICU are largely based on predefined threshold alarms and may have limitations in detecting more complex or subtle patterns of cardiorespiratory instability, as discussed in recent reviews [4,21].

ML models trained on cardiorespiratory signals have demonstrated promising performance for the early identification and prediction of apnea and hypoxia events in preterm infants. Varisco et al. developed ML approaches for the detection of central apnea using physiological signals [12], while Krupa et al. demonstrated the feasibility of DL-based models for automated identification of apnea and hypoxia patterns in neonatal respiratory data [32]. These findings highlight the potential of AI-based approaches to support enhanced respiratory monitoring and early recognition of instability in the NICU.

More broadly, recent reviews have emphasized that AI-enabled cardiorespiratory monitoring systems may support the identification of subtle physiological patterns not readily captured by conventional threshold-based monitoring, thereby offering potential opportunities for more individualized and proactive respiratory surveillance in neonatal intensive care settings [4,21,34].

6.5. AI in Ventilation Management and Extubation Readiness

Mechanical ventilation remains a cornerstone of neonatal respiratory support but is also associated with ventilator-associated lung injury and the subsequent development of BPD. Determining the optimal timing for extubation is particularly challenging in preterm

infants, as both premature and delayed extubation are associated with adverse respiratory outcomes [3,35].

To address this challenge, AI-based decision support tools have been developed to predict extubation readiness by integrating ventilatory parameters, blood gas values, and longitudinal physiological trends. Brasher et al. developed ML models for the prediction of extubation readiness in preterm infants, demonstrating promising predictive performance for identifying infants at risk of extubation failure [13]. More recently, Jenkinson et al. evaluated AI-based models specifically designed to predict extubation success in premature neonates and reported improved discriminative performance in identifying infants at higher risk of extubation failure, highlighting the potential clinical relevance of AI-assisted extubation planning in the NICU [20].

Beyond extubation readiness, AI has been increasingly applied to predict early respiratory deterioration that may require invasive mechanical ventilation. For example, recent clinical studies have explored ML-based approaches for early prediction of mechanical ventilation needs in very preterm infants, demonstrating that predictive models trained on early clinical and physiological data can identify infants at high risk of respiratory failure before clinical deterioration becomes apparent [36]. Using electronic health record-derived data, Kim et al. developed AI-based models capable of predicting the need for invasive mechanical ventilation early during NICU admission, demonstrating clinically meaningful predictive performance. Such early identification of high-risk infants may support closer monitoring and inform clinical decision-making regarding respiratory support escalation in neonatal intensive care settings [18].

Beyond invasive ventilation, recent AI applications have focused on predicting failure of non-invasive respiratory support, a critical and time-sensitive clinical problem in neonatal care. Delayed recognition of non-invasive ventilation failure may lead to worsening respiratory status and increased risk of lung injury. Contemporary reviews of non-invasive ventilation strategies emphasize that timely identification of NIV failure and appropriate escalation of care are central components of lung-protective respiratory management in preterm infants [35].

Using ML-based approaches, predictive models have been shown to identify infants at high risk of non-invasive respiratory support failure by analyzing early clinical variables and respiratory trends. In a recent study, Jeffreys et al. demonstrated that AI-driven models could achieve promising predictive performance in anticipating failure of non-invasive respiratory support in the neonatal unit, highlighting the potential of such tools to support earlier identification of high-risk infants and inform escalation of respiratory care [19].

In addition to predictive modeling, AI has been applied to procedural aspects of neonatal respiratory care, particularly airway management. Tracheal intubation remains a technically demanding and high-risk procedure in neonates, especially among extremely preterm infants and in emergency settings. Nakamura et al. described the development of an AI-assisted system integrated with video laryngoscopy to support tracheal intubation in infants and neonates, demonstrating the feasibility of real-time visual guidance during airway management and the potential to complement clinician expertise [36].

Complementing these system-level approaches, recent advances in DL-based computer vision have focused on improving the identification of key anatomical landmarks during neonatal intubation. Majeedi et al. developed a DL model capable of detecting the glottic opening in neonatal video laryngoscopy footage, achieving high accuracy in automated landmark recognition. Such approaches may enhance situational awareness during intubation, reduce failed or prolonged attempts, and further improve the safety and effectiveness of AI-assisted airway management in neonatal intensive care settings [37].

More broadly, ML models have also been applied to support early identification of infants at risk of respiratory deterioration or escalation of respiratory support. Recent studies have demonstrated that predictive models trained on early clinical and physiological data can identify infants at increased risk of requiring invasive mechanical ventilation during NICU admission [18,31]. Collectively, these applications underscore the expanding potential role of AI in supporting ventilatory and airway-related decision-making in neonatal care, with possible relevance for improving the individualization and safety of respiratory management.

6.6. Summary of Disease-Specific Applications

Collectively, the literature demonstrates that AI-based approaches have substantial potential across the spectrum of neonatal respiratory disorders. In RDS, AI-based methods have shown promising performance in supporting diagnosis and risk stratification using clinical and imaging data [7,8,16]. In BPD, ML models consistently enable early risk prediction, with potential relevance for identifying high-risk infants during a critical window for preventive strategies [9–11,15,17]. For apnea and respiratory instability, AI-based approaches support enhanced monitoring and early identification of cardiorespiratory instability using physiological signal analysis [4,12,32]. Finally, in ventilatory management, AI-based tools have been applied to support clinical decision support tasks, including prediction of extubation readiness and early identification of infants at risk of requiring escalation of respiratory support [13,18,20,32] (Table 1).

Table 1. AI applications in neonatal respiratory care.

Neonatal Respiratory Condition	AI Methodology	Data Sources	Clinical Application	Key References
RDS	DL, CNNs	Chest radiographs, lung ultrasound	Automated diagnosis, differentiation from other neonatal lung diseases, assessment of radiographic patterns	[7,8]
RDS	ML, ensemble models	Perinatal variables, early physiological data, ventilatory parameters	Early prediction of disease risk/severity and likelihood of escalation of respiratory support	[16,24]
BPD	ML, ensemble learning	Demographic data, oxygen exposure, ventilator settings, early clinical course	Early risk prediction and stratification prior to conventional clinical diagnosis	[9–11,17,26,27]
BPD	DL, longitudinal ML	Chest radiographs, clinical variables, longitudinal EHR data	Imaging-based risk prediction and incorporation of longitudinal data for outcome prediction	[9,15,28]
Apnea of prematurity	ML, DL	Cardiorespiratory signals, oxygen saturation, respiratory impedance	Detection and early identification of apnea and hypoxemia events	[12,32]
Respiratory deterioration	ML, early warning approaches	Continuous physiological monitoring, clinical variables	Early identification of infants at risk of respiratory deterioration or escalation of respiratory support	[18,31,34]
Mechanical ventilation and extubation	ML, clinical decision support models	Ventilator parameters, blood gas values, longitudinal physiological trends	Prediction of extubation readiness and identification of infants at risk of extubation failure	[13,20]
Non-invasive respiratory support failure	ML	Early clinical variables, respiratory trends	Prediction of failure of non-invasive respiratory support and identification of infants requiring escalation	[19]
Severe respiratory complications (e.g., pulmonary hemorrhage)	ML	Perinatal and early clinical variables	Early risk prediction for acute respiratory complications	[30]
Ventilator-associated pneumonia	DL	Clinical data, ventilator parameters	Early identification of ventilator-associated pneumonia in ventilated neonates	[33]

Abbreviations: AI, artificial intelligence; ML, machine learning; DL, deep learning; EHR, electronic health record; RDS, respiratory distress syndrome; BPD, bronchopulmonary dysplasia; CNNs, convolutional neural networks.

These disease-specific applications highlight the potential role of AI in advancing more individualized and data-informed respiratory care in the NICU, while also underscoring the importance of careful clinical integration. Among the reviewed applications, early prediction of BPD appears to represent the most clinically mature and extensively validated domain, whereas applications in apnea prediction and ventilatory management remain more heterogeneous in terms of methodology, validation, and implementation readiness.

7. AI in Respiratory Monitoring, Imaging, and Clinical Decision Support in the NICU

7.1. Limitations of Conventional Respiratory Monitoring in Neonates

Continuous respiratory monitoring is a cornerstone of neonatal intensive care; however, traditional monitoring systems rely primarily on fixed threshold-based alarms for parameters such as oxygen saturation, respiratory rate, and heart rate. Recent reviews have highlighted that such systems are limited in their ability to capture complex temporal physiological patterns and are associated with high false alarm rates, contributing to alarm fatigue and challenges in clinical workflow [4,21].

Furthermore, conventional monitoring approaches provide limited predictive insight, as they are largely designed to detect abnormalities only after physiological derangement has occurred. These limitations are particularly relevant in preterm neonates, whose immature respiratory control mechanisms predispose them to rapid and unpredictable cardiorespiratory instability [21,34]. AI-based monitoring systems have therefore emerged as a promising approach to address these challenges by enabling continuous, data-driven interpretation of respiratory and cardiorespiratory signals and supporting earlier identification of physiological instability [4,12,32].

7.2. AI-Driven Cardiorespiratory Monitoring Systems

Recent advances in ML have enabled the development of AI-driven cardiorespiratory monitoring platforms capable of analyzing high-frequency physiological data streams in real time. These systems integrate signals such as oxygen saturation, respiratory impedance, heart rate variability, and airflow to identify subtle deviations from baseline patterns that may precede clinical respiratory deterioration in neonatal populations [4,12,32].

AI-based monitoring frameworks have been proposed as an alternative to conventional threshold-based alarm systems, with reviews highlighting their potential to better capture complex temporal physiological patterns and support earlier recognition of instability [4,21]. Rather than relying on fixed alarm thresholds, such systems utilize continuous data-driven analysis to support more nuanced interpretation of physiological trends [34].

Wearable and non-invasive monitoring technologies further extend the capabilities of AI-driven cardiorespiratory surveillance. Reviews of AI-driven wearable technologies have highlighted advances in sensor design, signal acquisition, and AI-based signal processing that enable continuous monitoring with improved signal robustness and reduced susceptibility to motion-related artifacts [4,14]. These developments support the feasibility of longer-term, low-burden monitoring in neonatal populations.

Importantly, recent reviews have also suggested that AI-based monitoring approaches may contribute to reducing alarm fatigue by prioritizing clinically meaningful alerts and filtering out noise-related artifacts, thereby potentially improving workflow efficiency in the NICU [21,34]. When integrated into broader clinical decision support frameworks, such systems reflect a shift from purely reactive alarm-based surveillance toward more anticipatory, data-informed monitoring paradigms.

7.3. Prediction and Prevention of Apnea and Respiratory Deterioration

Apnea of prematurity and episodic respiratory deterioration remain major contributors to cardiorespiratory instability in NICU, particularly among preterm infants with immature respiratory control. Conventional monitoring systems are largely based on predefined alarm thresholds and typically detect apnea and desaturation events only after they have occurred, which limits opportunities for early identification of impending instability [4,21].

ML-based approaches trained on continuous cardiorespiratory signals have demonstrated promising performance for the early identification and prediction of apnea and respiratory instability in neonatal populations. Varisco et al. developed ML models for the detection of central apnea using physiological signals, demonstrating the feasibility of automated signal-based apnea identification [12]. More recently, Krupa et al. evaluated advanced DL and ML models, including CNNs, CNN-BiLSTM architectures, and random forest classifiers, applied to neonatal respiratory waveform data, and reported high performance in the automated identification of apnea and hypoxic events [32].

Collectively, these findings highlight the feasibility of non-invasive, AI-based analysis of physiological respiratory signals and support the potential role of such approaches in enabling earlier recognition of respiratory instability in the NICU [4,12,32].

More broadly, recent reviews have emphasized that AI-based monitoring systems may support a shift from purely reactive alarm-based surveillance toward more anticipatory, data-informed monitoring paradigms, although further prospective validation and clinical integration studies are required [21,34].

7.4. Integration of Wearable and Non-Invasive Technologies

Wearable and non-invasive respiratory monitoring technologies have gained increasing attention in neonatology due to their potential to reduce discomfort and skin injury in fragile infants and to facilitate less intrusive monitoring approaches. Reviews have highlighted that AI may play an important role in enhancing the performance of such devices by supporting signal processing, compensating for motion-related artifacts, and improving the reliability of physiological measurements [4,14].

A comprehensive review by Sitaula et al. emphasized the emerging role of AI-driven wearable technologies in neonatal cardiorespiratory monitoring, describing their potential for continuous and unobtrusive assessment of respiratory function both within and beyond the NICU setting [4]. Similarly, Grooby et al. discussed advances in wearable sensor design and feasibility considerations, supporting the concept that such technologies could be particularly valuable in settings where traditional monitoring infrastructure is limited [14].

More broadly, recent reviews have suggested that the integration of AI with wearable sensors may facilitate longitudinal respiratory monitoring and support earlier identification of evolving physiological changes, although further validation studies and real-world implementation data are still required [5,21,34].

7.5. AI-Assisted Imaging Beyond Diagnosis

While AI-assisted imaging has been extensively explored for diagnostic classification, recent studies and reviews have suggested a broader potential role for imaging-based AI tools in supporting assessment of disease evolution and severity in neonatal respiratory disorders. DL models applied to chest radiographs and lung ultrasound images have demonstrated the ability to extract imaging features associated with respiratory pathology and risk of adverse outcomes, supporting the concept that imaging-based AI may contribute to longitudinal assessment when applied to serial studies [9,15,28].

Chou et al., for example, developed a DL model using chest radiographs from preterm infants and demonstrated that imaging features extracted by the model were predictive

of subsequent BPD, highlighting the potential of AI-based imaging approaches to capture clinically relevant patterns beyond single time-point diagnosis [28].

Recent reviews have emphasized that AI-assisted image analysis may support more consistent and objective interpretation of neonatal imaging compared with purely subjective assessment, which is known to be affected by interobserver variability, and could therefore facilitate more reproducible assessment of respiratory disease severity over time [5,7,8,15].

7.6. Clinical Decision Support Systems in Neonatal Respiratory Care

Beyond monitoring and imaging applications, AI has increasingly been explored within clinical decision support systems to assist clinicians in managing complex care decisions in NICU. Systematic reviews evaluating AI-based decision support in neonatal and pediatric critical care have highlighted the potential of such systems to support clinical decision-making and care efficiency, while also emphasizing considerable heterogeneity in study quality, validation, and implementation readiness [6,21].

These decision support systems are designed to synthesize heterogeneous data sources—including electronic health records, continuous physiological monitoring, and imaging data—to generate data-informed outputs intended to augment, rather than replace, clinical judgment [5,22]. Reviews focusing on clinical integration emphasize that clinician engagement and interpretability are central to the safe and effective use of AI-driven decision support in real-world NICU environments [22,38].

Building on this paradigm, AI-based predictive tools have been developed to estimate clinically relevant outcomes such as length of stay, morbidity, and resource utilization in neonatal intensive care populations. Tudor et al. summarized that ML models using routinely collected clinical data demonstrate promising performance for outcome prediction [34], while Xie et al. developed and validated a large-scale, multicenter pretrained language model using neonatal EHR data that demonstrated robust predictive performance across multiple neonatal outcomes, including respiratory morbidity [25]. Such approaches illustrate the potential of longitudinal EHR-based modeling to support earlier identification of high-risk infants and anticipatory care planning.

Emerging applications of AI-driven decision support also extend beyond ventilatory management to more complex therapeutic decisions. Bottu and Manzar discussed the potential role of AI-assisted frameworks in supporting postnatal corticosteroid decision-making in extremely preterm infants by integrating respiratory severity, ventilatory dependence, and individualized risk profiles, highlighting the conceptual value of such tools for supporting nuanced clinical judgment in challenging therapeutic contexts [39].

At a broader systems level, reviews addressing implementation challenges in neonatal AI have emphasized that the clinical impact of AI-based decision support tools is strongly influenced by factors such as scalability, interoperability with existing hospital information systems, model transparency, and clinician trust. Several authors have highlighted that respiratory applications represent a particularly promising domain for clinical translation, given the continuous availability of relevant physiological data and the central role of respiratory management in neonatal outcomes, while underscoring the need for prospective validation and careful workflow integration [5,22,38].

7.7. Ethical, Practical, and Implementation Considerations

Despite the growing promise of AI-driven respiratory monitoring and decision support, several challenges continue to limit widespread clinical adoption. Reviews have consistently highlighted issues related to model interpretability, data quality, and generalizability across different neonatal populations and healthcare settings as key barriers to implementation [5,21,34].

Ethical considerations, including data privacy, algorithmic bias, transparency, and clinician accountability, are particularly salient in neonatal care. Sullivan et al. emphasized the need for robust governance frameworks, transparent model development, and appropriate regulatory oversight to ensure the safe and equitable deployment of AI technologies in the NICU [38].

Importantly, multiple authors have emphasized that AI tools should be conceptualized as augmentative rather than replacement technologies. Vijlbrief et al. highlighted the importance of clinician involvement throughout model development and implementation [22], while Sensi et al. demonstrated that clinicians consistently view AI as most acceptable when positioned as a supportive tool that enhances, rather than replaces, professional judgment [40]. Together, these findings underscore the need for close collaboration between clinicians, data scientists, and healthcare systems to achieve meaningful clinical integration.

Collectively, the literature indicates that AI-based approaches have expanded the scope of respiratory monitoring, imaging analysis, and clinical decision support in neonatal intensive care (Table 2). While current evidence primarily demonstrates feasibility and promising performance rather than definitive outcome improvement, these technologies hold substantial potential to support earlier identification of respiratory instability, more informed therapeutic decision-making, and more individualized approaches to neonatal respiratory care [5,21,38].

Table 2. AI-enabled respiratory monitoring and decision support in the NICU.

Application Domain	AI Approach	Clinical Purpose	Potential Benefits	Representative Studies	Key Challenges/Limitations
Cardiorespiratory monitoring	ML, DL	Detection of subtle respiratory and cardiorespiratory instability	Earlier identification of physiological instability; improved interpretation of complex signal patterns Reduced patient burden; improved signal robustness; feasibility for longer-term monitoring	[4,12,21,32,34]	Limited external validation; integration into real-time workflows remains challenging
Wearable and non-invasive monitoring	AI-enhanced signal processing, ML	Continuous respiratory and oxygenation assessment	Earlier recognition of instability; potential support for proactive monitoring Improved consistency of interpretation; reduced subjectivity; potential for longitudinal assessment	[4,14,21]	Device variability; motion artifacts; limited large-scale neonatal validation
Apnea and hypoxemia prediction	ML, DL	Identification and early recognition of apnea and hypoxemic events	Data-informed decision support; potential to improve consistency of care Improved identification of infants at risk of extubation failure	[4,12,32]	Predominantly retrospective datasets; few prospective implementation studies
Imaging-based respiratory assessment	DL, CNNs	Objective assessment of lung pathology and severity	Earlier identification of high-risk infants; potential support for care planning	[7–9,15,28]	Limited multicenter validation; variability in imaging acquisition protocols
Clinical decision support systems (CDSS)	ML, EHR-based predictive models	Support for complex clinical decision-making and outcome prediction		[6,21,22,25]	Workflow integration and clinician adoption remain insufficiently evaluated
Ventilation and extubation decision support	ML, longitudinal predictive models	Prediction of extubation readiness		[13,20]	Small cohorts; lack of prospective randomized validation
System-level planning and outcome prediction	Predictive analytics, EHR-based models	Length of stay forecasting and outcome prediction		[21,25,34]	Outcomes influenced by institutional factors; generalizability across settings uncertain

Abbreviations: AI, artificial intelligence; ML, machine learning; DL, deep learning; CDSS, clinical decision support systems; EHR, electronic health record; NICU, neonatal intensive care unit; CNNs, convolutional neural network.

8. Clinical Integration, Limitations, Ethical Considerations, and Future Directions

8.1. Clinical Integration of AI in Neonatal Respiratory Care

Despite the rapid expansion of AI-based applications in neonatal respiratory medicine, translation from research settings to routine clinical practice remains limited. Successful clinical integration of AI tools in the NICU requires careful alignment with existing workflows, interoperability with hospital information systems, and clinician acceptance [34,38].

Respiratory applications are particularly well-suited for early clinical deployment, given the continuous availability of high-resolution physiological data, ventilator parameters, and imaging studies. However, AI systems must be seamlessly embedded within clinical workflows to provide timely, interpretable outputs that support real-world decision-making rather than disrupt established care processes [4,5,14]. Studies evaluating AI-driven clinical decision support systems emphasize that tools delivering clear risk stratification or actionable recommendations at the point of care are more likely to be adopted and sustained [6,22,40].

Importantly, integration efforts should prioritize usability and clinician engagement. Human-centered design approaches and iterative feedback from neonatal care teams are essential to ensure that AI tools address clinically meaningful questions and align with the realities of NICU practice [22,38,40].

8.2. Methodological and Practical Limitations

Several methodological challenges continue to limit the widespread adoption of AI in neonatal respiratory care. First, as this is a narrative review, the study selection process is inherently subject to selection bias, and no formal risk-of-bias or quality assessment of the included studies was performed. This represents an important limitation of the present work and should be considered when interpreting the overall strength of the evidence.

A major limitation of the current literature is the predominance of retrospective, single-center study designs, which raises substantial concerns regarding generalizability and external validity across heterogeneous neonatal intensive care unit populations and healthcare systems [5,6,21,34]. Although recent multicenter studies using large real-world datasets—such as ML models trained across multiple hospitals in the United States for respiratory outcome prediction [31] and large-scale neonatal language models validated on multi-institutional cohorts [25]—demonstrate that broader geographic validation is feasible, such studies remain relatively limited in number compared with single-center reports. Moreover, many published datasets continue to originate from geographically concentrated populations, with a notable overrepresentation of East Asian cohorts, which may further restrict the transferability of findings to other clinical settings.

Data quality constitutes an additional critical challenge, as neonatal datasets are frequently affected by missing values, signal artifacts, and variability in clinical practice patterns. While advanced ML techniques may partially mitigate these limitations, robust data preprocessing, transparent reporting, and standardized methodological frameworks remain essential to ensure model reliability, reproducibility, and meaningful comparison across studies [6,34,38]. For example, recent DL approaches applied to neonatal respiratory waveform analysis for automated hypoxia and apnea detection demonstrate promising technical performance but are primarily evaluated on relatively limited datasets, without large-scale multicenter external validation, highlighting the gap between methodological innovation and robust clinical generalizability [12,32].

Moreover, despite promising predictive and diagnostic performance, many AI-driven respiratory tools lack prospective clinical validation and systematic evaluation of real-world clinical impact. There remains limited critical comparison between competing models,

with few studies performing head-to-head comparisons using standardized datasets, harmonized outcome definitions, or shared benchmarking frameworks, and relatively few studies provide concrete pathways for clinical implementation. Insufficient assessment of workflow integration, clinician interaction, and patient-centered outcomes continues to hinder confident translation into routine practice [22,34,38,40]. In addition, the increasing use of complex DL architectures raises concerns regarding interpretability and explainability, which may affect clinician trust, accountability, and ethical deployment.

Collectively, these limitations underscore the need for multicenter collaboration, greater geographic diversity in training datasets, standardized methodological frameworks, and prospective implementation studies to support safe, effective, and equitable integration of AI into neonatal respiratory care. An overview of representative studies, including study design, validation status, and clinical readiness of AI models in neonatal respiratory care, is provided in Table 3.

Table 3. Study characteristics and validation status of key AI models in neonatal respiratory care.

Study (Reference)	Respiratory Application	Study Design	Data Sources	Validation Type	Clinical Readiness
Yoneda et al. [11]	Death or BPD prediction at birth	Nationwide retrospective cohort	National neonatal database (Japan)	Internal	Moderate–High
Jang et al. [16]	RDS severity prediction	Prospective, multicenter cohort	Perinatal and early clinical data	External, multicenter	High
Verder et al. [17]	BPD prediction at birth	Retrospective cohort	Perinatal variables	Internal	Moderate
Jeffreys et al. [19]	Non-invasive ventilation failure	Retrospective cohort	Early respiratory and clinical variables	Internal	Early
Jenkinson et al. [20]	Extubation readiness	Retrospective cohort	Ventilator and physiological data	Internal	Moderate
Xie et al. [25]	Multi-outcome prediction (including BPD, RDS)	Retrospective multicenter cohort	Large-scale multi-institutional EHR datasets (USA)	External validation	Moderate–High
Lei et al. [27]	BPD risk stratification	Retrospective cohort	Clinical variables	Internal	Moderate
Aly et al. [30]	Pulmonary hemorrhage prediction	Retrospective cohort	Perinatal and early clinical data	Internal	Early
Gates et al. [31]	Early prediction of mechanical ventilation	Retrospective cohort	Clinical and physiological data	Internal	Moderate
Krupa et al. [32]	Apnea and hypoxia detection	Retrospective cohort	Respiratory waveform signals	Internal	Early
Hsu et al. [33]	Ventilator-associated pneumonia	Retrospective cohort	Clinical, ventilator, and imaging data	Internal	Early
Bottu and Manzar [39]	Postnatal steroid decision support	Conceptual/exploratory	Clinical and ventilatory profiles	Not applicable	Exploratory

Abbreviations: BPD, bronchopulmonary dysplasia; RDS, respiratory distress syndrome; EHR, Electronic health record.

8.3. Interpretability, Ethics, and Regulatory Considerations

Interpretability remains a central challenge in the application of AI to neonatal respiratory care. Although complex “black-box” models may achieve high predictive or diagnostic accuracy, limited transparency in model decision-making can undermine clinician trust, impede clinical adoption, and complicate accountability in high-stakes neonatal settings [22,34,38,40].

Importantly, early applications of explainable AI are emerging in neonatal research. For example, explainability techniques such as SHapley Additive exPlanations (SHAP) have been applied to neonatal outcome prediction models to identify and visualize the contribution of individual clinical features to model predictions, including for outcomes such as RDS. These approaches provide greater transparency into model behavior and offer clinicians more interpretable insights into why specific predictions are generated, representing an important step toward improving trust and clinical acceptability of AI-based tools in neonatology [41].

In addition, recent work has evaluated the use of visualization-based explainability methods such as Gradient-weighted Class Activation Mapping (Grad-CAM) for breath classification using neonatal respiratory time-series data, illustrating how DL model decisions can be made more interpretable in neonatal respiratory applications [42]. Collectively, these approaches represent important early steps toward improving interpretability, clinician trust, and the clinical acceptability of AI-based tools in neonatology.

Ethical considerations are particularly salient in neonatal medicine, where patients are uniquely vulnerable and clinical decisions may have lifelong implications. Issues related to data privacy, informed consent, algorithmic bias, and fairness require careful consideration, especially when AI systems are trained on datasets that may not fully represent diverse neonatal populations or care environments [34,38,40]. Ensuring responsible and equitable deployment of AI-driven respiratory tools, therefore, necessitates ongoing ethical oversight and multidisciplinary collaboration.

Regulatory frameworks for medical AI are evolving in parallel with rapid technological advances. Recent reviews emphasize the importance of aligning AI development with emerging regulatory standards and ensuring transparency in model validation, performance reporting, and clearly defined limitations prior to clinical implementation [21,34,38]. Within this context, AI systems should be positioned as clinical decision-support tools that augment clinician expertise and judgment, rather than as autonomous decision-makers, particularly in the complex and high-risk environment of neonatal intensive care.

8.4. Future Directions and Research Priorities

Future research in AI-driven neonatal respiratory care should prioritize prospective validation, multicenter collaboration, and the integration of multimodal data sources. Combining continuous physiological monitoring, ventilator-derived parameters, medical imaging, and longitudinal electronic health record data may further enhance predictive accuracy, robustness, and clinical relevance, while improving generalizability across diverse neonatal populations and care settings [5,21,34,38].

The development of explainable AI models represents a key research priority, as transparent and interpretable outputs are essential for clinician trust, ethical accountability, and safe clinical adoption. In parallel, future studies should rigorously evaluate the impact of AI-driven tools on clinically meaningful outcomes, including the duration of respiratory support, the incidence of BPD, and the length of NICU stay, using prospective, implementation-focused study designs. Broader systematic evaluations of AI applications in neonatal and pediatric intensive care similarly emphasize the need for standardized methodological frameworks, external validation, and careful assessment of real-world clinical impact prior to widespread deployment [6,21,34,38].

Successful translation of AI into neonatal respiratory care also depends on meaningful clinician involvement throughout model development and implementation. Close collaboration between data scientists and neonatologists, with attention to co-design, interpretability, and alignment with clinical workflows, is critical to ensure trust, usability, and safe bedside adoption of AI-driven tools [22,38,40].

Finally, the equitable and sustainable deployment of AI technologies across diverse healthcare environments—including resource-limited settings—should remain a central consideration. Reviews of future directions in neonatal AI consistently identify respiratory applications as among the most promising and scalable use cases, provided that implementation strategies are context-sensitive, interoperable, and ethically grounded [5,34,38]. Emerging approaches that extend AI-driven respiratory decision support beyond the NICU, such as conversational agents and chatbot-based platforms for chronic neonatal

lung disease and home oxygen therapy management, further highlight the potential of AI to improve continuity of care and caregiver engagement following hospital discharge [29].

9. Conclusions

AI has increasingly emerged as an important adjunct in the diagnosis, monitoring, and management of neonatal respiratory disorders, with applications spanning RDS, BPD, apnea of prematurity, ventilator management, and respiratory complications. By integrating physiological data, ventilator parameters, medical imaging, and electronic health records, AI-based approaches have the potential to enable earlier risk stratification, support personalized respiratory care, and enhance clinical decision-making in the neonatal intensive care unit. While expectations for AI-driven respiratory care are high, the ultimate clinical impact will depend on rigorous prospective validation, sustained clinician engagement, and careful integration into real-world neonatal practice. Despite ongoing challenges related to validation, interpretability, and ethical implementation, the growing body of evidence indicates that AI represents a promising step toward precision respiratory medicine in neonatology, provided that its integration into clinical workflows is guided by rigorous evaluation and interdisciplinary collaboration.

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