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# Artificial Intelligence (AI) Improves Patient Outcomes in Neonatal Intensive Care Units: Challenges and Future Directions

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## Abstract

**Background**: Pediatric intensive care units (PICUs) could transform due to artificial intelligence (AI), which could improve patient outcomes, increase diagnostic accuracy, and streamline repetitive procedures. The goal of this systematic review was to represent one of the first comprehensive efforts to explore the application of AI in improving patient outcomes in PICUs.

**Methods**: We searched four databases (PubMed, Scopus, Web of Science, and IEEE Xplore) for relevant studies using a predefined systematic search using several words like AI, neonatal ICU, PICUs, the studies were further screened based on inclusion and exclusion criteria in this study.

**Results:** Artificial intelligence technologies are increasingly used in pediatrics and have the potential to help inpatient physicians provide high-quality care for critically ill children. There are not sufficient studies showing that AI has significantly enhanced pediatric critical care patients' health outcomes. To evaluate AI's impact, more prospective, experimental research is required, utilizing verified outcome measures, defined metrics, and established application frameworks.

**Keywords:** Artificial Intelligence; Augmented Reality; Documentation; Intensive Care Units; Neonatal Outcomes

**Abbreviations:** LLMs: Large Language Models; EHRs: Electronic Health Records; AI: Artificial Intelligence; LLMs: Large Language Models; ML: Machine Learning; IVH: Intraventricular Hemorrhage; CDS: Clinical Decision Support; TPN: Total Parenteral Nutrition

## Background

Artificial intelligence (AI), motivated by its potential to enhance patient outcomes and assist professional judgments, is poised to significantly transform medicine, as evidenced by the notable rise in research studies, particularly in critical care medicine [1]. This expansion is reflected in the growing number of clinical studies on AI-related themes [2]. Additionally, generative AI is becoming more popular in healthcare settings, especially with large language models (LLMs) like ChatGPT, which help with communication and documentation duties and support decision-making. Healthcare professionals' initial opinions of ChatGPT in pediatric critical care emphasize both its advantages and disadvantages [3].

Despite the challenges in research caused by ethical and practical issues, AI may assist doctors with diagnosis, prognostics, and treatment in pediatric intensive critical care to enhance patient outcomes [4]. However, a lot more work needs to be done before the results of AI research are used at the patient's bedside and become a true clinical benefit. The influence of AI models in the actual world is currently limited because less than 2% of them make it past the prototype stage [5]. Since most of the patients in this research are adults and bias are a significant issue for AI models, it is unclear how these results relate to pediatric populations. Each group has distinct clinical needs, assessments, and treatment approaches due to the notable variations in disease incidence, presentation, outcomes, and prognosis among youngsters [6]. Therefore, creating AI models especially suited to pediatric care is imperative to closing this gap.

## Clinical Influence and Readiness of AI

Even though some experts believe AI will revolutionize healthcare in the future, most new AI technologies have not yet been adopted by the larger medical community. Not every technological development produces tools fit for daily use [7]. Although artificial intelligence (AI) has advanced significantly in adult medicine, especially in critical care and inpatient settings, its application in pediatric care is still in its infancy [8]. Prior to being incorporated into standard clinical practice, AI applications in healthcare must pass stringent testing, just like other medical devices and treatments [9,10].

Concerns regarding the safety and efficacy of these tools and techniques in particularly vulnerable populations, such premature babies, could cause the use of AI in pediatric critical care to lag other medical disciplines. There isn't much research on the use of AI in low- to middle-income countries, where a lot of newborns and young children require emergency treatment [11-13]. The effect of AI on these clinical settings and its consequences for patient care and healthcare procedures are crucial topics for further study.

## ML Applications in Neonatal Mortality

One of the main causes of child death is neonatal mortality. According to the World Health Organization, 47 percent of all deaths in children under five are neonatal deaths [14]. Therefore, reducing global infant mortality by 2030 is a top objective [15]. The causes of infant mortality and its prediction were examined by machine learning (ML) [16,17]. 1.26 million babies delivered between 22- and 40-weeks' gestation were included in a recent review [18]. As early as five minutes of life and as late as seven days, predictions were made. Neural networks, random forests, and logistic regression accounted for an average of four models per study (58.3%) [18]. Five research (45.5%) published calibration plots, while two studies (18.2%) finished external validation [18]. According to research, heart rate variability can predict early sepsis with an accuracy of 64–94% [19]. Clinical biomarkers balanced the ML decision by incorporating all clinical and lab characteristics, and they reached an AUC of 73–83%, according to another secondary analysis of multicenter data [20].

## ML Applications in Predictions of Prematurity Complications (BPD, PDA, And ROP)

PDA, or patent ductus arteriosus, is another significant cause of death and morbidity in the NICU. ML techniques were used to detect PDA using EHR and auscultation records, resulting in a 76% prediction of PDA from 47 perinatal parameters assessed using 5 distinct ML techniques in 10390 extremely low birth weight infants. When XG Boost was used to evaluate auscultation records 123 and 250, the accuracy was 74% (Gomez-Quintana S, et al. 2021). There are ML studies aimed at predicting BPD from birth, gastric aspirate content, and genetic data, and it has been shown that BPD can be predicted with an accuracy of up to 86% in the best-case scenario, analysis of responsible genes with ML can predict BPD development with an AUC of 90%127, and the combination of gastric aspirate after birth and clinical information analysis with SVM can predict BPD development with a sensitivity of 88% [21].

## Neonatology with Deep Learning

The primary applications of DL in clinical image analysis are divided into three categories: classification, detection, and segmentation. Classification identifies a specific feature in an image, detection locates numerous features inside an image, and segmentation divides an image into multiple pieces [22,23].

## Prematurity Complications with DL in Neonatology

Digital imaging and AI-powered analysis are promising and cost-effective approaches for identifying infants with severe ROP who may require treatment. DL has been used to analyze neonatal EEGs and determine sleep stages. Interruptions in sleep have been linked to issues with neural development [24]. DL was used to demonstrate automated sleep state recognition using EEG records and ECG monitoring parameter data. The underperformance of the all-state classification (kappa score 0.33 to 0.44) was most likely due to difficulty in identifying modest changes between states and a lack of sufficient training data for minority classes.186.

DL has been shown to be helpful in real-time evaluation of cardiac MRI for congenital heart disease [25]. Neonatal illnesses have been classified using deep learning algorithms based on thermal imaging. This research evaluated neonatal thermograms to determine infant health status and achieved high AUC values. However, these trials lacked clinical information. Two large-scale studies revealed ground-breaking findings about the impact of dietary practices and wireless sensors in NICU. A nutritional study found that nutritional behaviors were linked to discharge weight and BPD. This demonstrates how impartial ML approaches can be utilized to effectively implement clinical practice modifications. Novel wireless sensors can improve monitoring, reduce iatrogenic injuries, and promote family-centered treatment [26].

## Informatics and AI in NICU Resuscitation

### Clinical Deterioration Prediction

AI-powered systems can detect these changes, notify physicians immediately, and enable more effective and fast assessment and action. The HeRO® monitoring system was the first AI risk-scoring system designed for the NICU that predicted clinical deterioration (e.g., late-onset sepsis and necrotizing enterocolitis) using heart rate variability trends [27]. Several AI-enabled software platforms process real-time, continuous physiological data from cardiorespiratory devices. These platforms use machine learning approaches to provide clinical decision support (CDS). Novel models based on these data, such as the Hyperlactatemia Index, accurately predicted elevated lactate levels and the probability of poor cardiac output in pediatric critical care patients [28].

## Resuscitation Education and Simulation

### Virtual Reality (VR), Augmented Reality (AR) And Gamification

Neonatal resuscitation education improves technical skills and teamwork among healthcare workers. Originally used with real-


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world elements such as manikins, it has progressed with computer technology to encompass virtual and hybrid settings. Figure 1 depicts the reality-virtual continuum in neonatal resuscitation scenarios, demonstrating a trend toward immersive technology in resuscitation training [29]. Neonatal resuscitation manikins, such as NeoNatalie™, provide tailored learning experiences using AI analysis [30]. They offer real-time input on bag-mask ventilation. With autonomous operation, learners can practice individually while receiving feedback on specific areas for growth. Further VR advancements with lifelike scenarios will increase engagement, knowledge retention, and skill development. Remote coaching via simulated neonatal resuscitation greatly improves care [31]. Telesimulation extends high-quality resuscitation training to even remote places in low-resource settings, and it tracks learners' progress over time.

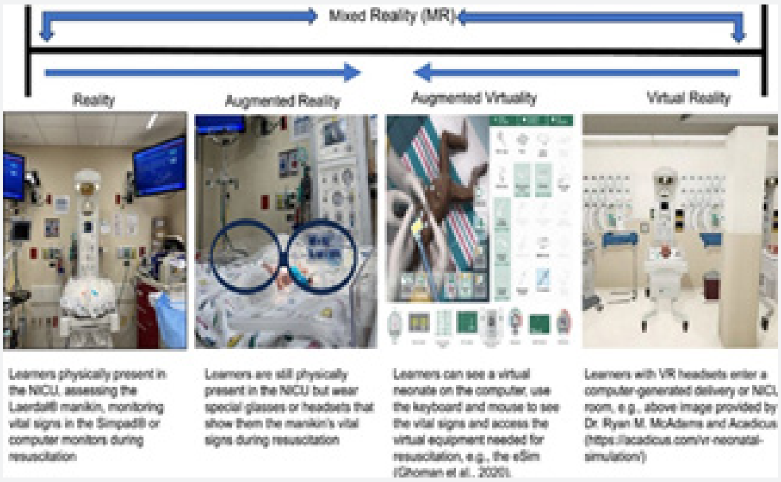


**Figure 1:** Milgram and Kishino's reality-virtuality continuum with neonatal resuscitation examples.

## AI in Resuscitation Education

Individualized, "on demand" education can be improved by combining AR, VR, and generative AI. More realistic simulations will be used to teach teams in crew resource management and communication [32]. Resuscitation training is one of the earliest instances of VR and AI being used in staff training for sepsis care using AI medical team members [33]. Combining AR and generative AI to place cues in a trainee's field of vision during exercises could improve verbal and nonverbal communication abilities. By aiding clinical decision-making, enabling simulation-based training, and offering multilingual instructional materials, artificial intelligence (AI) has the potential to enhance newborn resuscitation and teaching. To improve clinical skills and provide individualized learning experiences, LLMs can be incorporated into training programs [34].

## AI-Guided Precision Parenteral Nutrition for Neonatal Intensive Care Units

Making treatment decisions based on computational techniques that utilize data repositories, such continuous monitor recordings and electronic health records (EHRs), is another new frontier in NICU innovation brought about by the rise of big data and artificial intelligence. Numerous predictive models are already showing progress, such as those for identifying intraventricular hemorrhage (IVH) or neonatal infection [35,36]. Even with these developments, AI's full potential is still mostly unrealized. Clinical AI use is still only 10% in many US hospitals [37], with radiology and cardiology accounting for nearly 90% of adoption and neonatology for 0% [38].

Many prediction models do not affect outcomes in actual clinical settings, even when they are highly accurate [39]. As evidenced by new developments like large action models in autonomous systems, which prioritize actionable outcomes for increased clinical impact, this highlights the need for clinically relevant AI that goes beyond prediction-making to guide successful [40,41]. The necessity for targeted interventions is highlighted by the fact that one in ten newborns are admitted to neonatal intensive care units. Nevertheless, nothing is known about how artificial intelligence (AI) might be used to direct newborn care. For premature infants, total parenteral nutrition (TPN) is a life-saving treatment; nevertheless, the therapy's present application is resource-intensive, subjective, and prone to errors.

TPN2.0, a data-driven method that optimizes and standardizes TPN utilizing data typically gathered from electronic health records, was created by Phongpreecha et al. [42]. To train TPN2.0, they gathered ten years' worth of TPN compositions (79,790 orders; 5,913 patients) at Stanford. They verified their model in


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an external cohort (63,273 orders; 3,417 patients) from a second institution in addition to their internal validation. Their system found 15 TPN formulas that can increase safety and possibly save costs by enabling a precision-medicine approach (Pearson's R = 0.94 compared to experts). Physicians evaluated TPN2.0 higher than current best practice, according to blind research (n = 192). Standard prescriptions were linked to higher morbidities (for instance, odds ratio = 3.33; P value = 0.0007 for necrotizing enterocolitis) in patients where there was a large degree of disagreement between the actual prescriptions and TPN2.0, but TPN2.0 recommendations were linked to lower risk. Lastly, we showed how TPN2.0's transformer architecture allowed physician-in-the-loop, guideline-adhering suggestions that facilitate AI and care team cooperation (Figure 2).

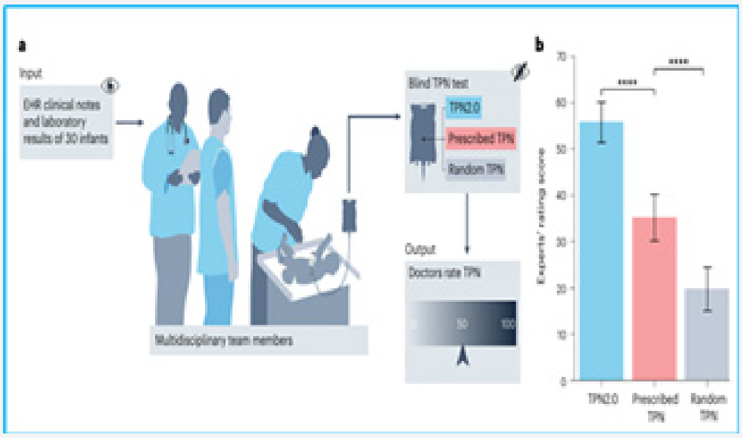


**Figure 2:** In a blind study, TPN2.0 outperformed the current best practice. a, in a blinded study, physicians who regularly prescribe TPN were recruited to rank three TPN solutions: TPN2.0, TPN composition from a different patient (randomly selected) and the actual prescription developed for that patient according to current best practice. Each team member ranked each of the three solutions from 0 to 100 after a thorough chart based on all information available in their EHR. The higher rating indicates a more appropriate composition. b, from a total of n = 192 comparisons from ten healthcare team members, TPN2.0 received the highest experts' rating scores. The scores are also significantly higher (Mann–Whitney U test, two-sided P value.

## Challenges and Future Directions in AI for Pediatric Intensive Care

AI systems need to be able to analyze and decode gigabytes of clinical data to function as effective decision support systems and help intensivists in real time [43]. It's interesting to note that while critical care is the focus of the analysis, several of these problems may also exist in pediatric inpatient settings. A significant barrier to the use of AI technology is the fact that the data from hospitalized patients that is needed for interpretation and training is typically complex, varies throughout institutions, and is largely unstructured. Even while digital data is now more easily accessible for analysis, it is not regularly gathered, accurately measured, and recorded [44]. For unstructured text data, such clinical notes in most inpatient settings, natural language processing (NLP) is necessary [45].

Unfortunately, annotating large text passages to train any model is expensive and time-consuming. NLP was only employed in one article in our review, suggesting that AI developers working in neonatal and pediatric intensive care settings are still learning about this technology [46]. The results of our review are less replicable since the studies do not evaluate bias in the data itself or deal with strategies for handling skewed or unbalanced data. Structured data-trained algorithms can improve AI performance, provide high-quality data extraction, and facilitate the use of AI input. Future studies might investigate the concept of "representation learning." In representational learning, AI models use a prediction model and automatically learn characteristics to create an abstract representation of each patient's data for medical record extraction.

AI integration in neonatal and pediatric critical care may be more challenging due to several human factors and system-integration challenges in addition to technical limitations. Future studies should focus on the factors that influence clinician trust in AI and look at how AI impacts clinical workflow. The use of AI may cause providers to acquire cognitive biases over time. For instance, because of the AI system's dependable and highly efficient performance, clinicians may begin to accept its data without question, or because of their past experiences, they may reject AI output data without fully evaluating how it might impact outcomes. Quantitatively speaking, AI trained on a certain patient subset may be biased and produce results that are only applicable to that patient group. To overcome these obstacles, future researchers will need to engage the help of human factors engineers, computer scientists, and medical professionals.

Crucially, future research is the only way to determine AI's utility because its accuracy is anticipated to decline as it encounters


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real-world data that differs from algorithm training [11,47]. Finally, most of the research reduced pediatric problems to binary classification types, employing a number of characteristics to assign a person to one of two groups (sickness vs. no illness) [48-50]. The potential that a patient may have multiple comorbidities, each with differing degrees of severity or interdependency, is disregarded by this approach. Since the methodology of this research rarely addresses the barriers to adopting AI, we did not summarize or analyze these factors in our study. This is another important topic that requires further research [51-54].

## Summary and Conclusions

Resuscitation care in neonatal intensive care units is constantly changing and depends more on data. Artificial intelligence and informatics tools can be used to support data-driven precision resuscitation care. Because of poor data collection, aggregation, and limited adoption of artificial intelligence and analytical tools, these data are frequently underutilized despite technological breakthroughs. To support neonatal intensive care unit resuscitation care, training, and teaching, this review outlines the principles and investigates the evidence supporting informatics and artificial intelligence solutions. The necessity of an efficient interface design for precise data collection, storage, and conversion to wisdom using analytics and AI tools is one of the main conclusions. When using these tools, this review discusses data privacy, bias, responsibility, and ethical frameworks.

Even though these new technologies have a lot of potential to enhance resuscitation, more research on their use in neonatal populations is necessary, as is clinical comprehension of informatics and artificial intelligence concepts. It will take some time before AI is broadly incorporated into standard pediatric healthcare procedures, even though there is a growing body of evidence supporting its use to improve pediatric health outcomes. For instance, there are difficulties when applying supervised AI algorithms to inpatient data since AI generally has trouble processing unsupervised data for clinical data extraction, and input training on trained models prevents effective use of AI in real-world scenarios (like complex critical illnesses with comorbidities). To fully exploit the potential benefits of AI in pediatric healthcare facilities, more study is required.

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