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Artificial intelligence and informatics in neonatal resuscitation

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A R T I C L E I N F O

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Neonatal intensive care unit resuscitative care continually evolves and increasingly relies on data. Data driven precision resuscitation care can be enabled by leveraging informatics tools and artificial intelligence. Despite technological advancements, these data are often underutilized due to suboptimal data capture, aggregation, and low adoption of artificial intelligence and analytic tools. This review describes the fundamentals and explores the evidence behind informatics and artificial intelligence tools supporting neonatal intensive care unit resuscitative care, training and education. Key findings include the need for effective interface design for accurate data capture followed by storage and translation to wisdom using analytics and artificial intelligence tools. This review addresses the issues of data privacy, bias, liability and ethical frameworks when adopting these tools. While these emerging technologies hold great promise to improve resuscitation, further study of these applications in neonatal population and awareness of informatics and artificial intelligence principles among clinicians is imperative.

Introduction

Approximately 2 % of patients in level 4 Neonatal Intensive Care Units (NICU) require resuscitation during their hospitalization, an incidence 10 times that of newborns in the delivery room.[1] Informatics tools, including artificial intelligence (AI), are uniquely positioned to advance NICU resuscitative care through improved data management, including data capture, retrieval, sharing, analysis, visualization, and learning. Awareness of the current limitations and opportunities for future innovation in this field is crucial, as they will shape the future of neonatal care.

AI, an emerging tool, gained significant momentum in the last decade across various industries, including healthcare, fueled by increased computational power and expanded data storage.[2] Despite the promise and potential for AI in healthcare, utility in neonatal care, specifically neonatal resuscitation, is currently quite limited and largely unproven. This paper describes the fundamentals of informatics and AI and their applications in real-time care to ethically and safely improve neonatal resuscitation.

Informatics fundamentals

Progression from data to wisdom

The Data-Information-Knowledge-Wisdom framework describes the progress of effective data use.[3] Data are single measurements, such as heart rate and rhythm. Combining data can reveal information, like a heart rate trend or pulseless electrical activity, creating actionable or important knowledge. The knowledge that hyperkalemia can cause pulseless activity can lead to the wisdom that addressing risk factors can prevent abnormal rhythms.

Sources and types of data

Sources of raw data include physiological monitors (e.g., heart rate, oxygen saturations), medical devices (e.g., ventilators, syringe pumps, and defibrillators), and health records (e.g., diagnosis codes, notes, labs, orders, resuscitation events, and imaging). Data may be validated with clear data types and sources or unvalidated (e.g., the numeric fraction of inspired oxygen direct from a ventilator interface versus typed into an

Abbreviations: AI, Artificial Intelligence; AR, Augmented Reality; CDS, Clinical Decision Support; DL, Deep Learning; EHR, Electronic Health Record; GWTG-R, Get with the Guidelines Resuscitation; LLM, Large Language Model; NICU, Neonatal Intensive Care Unit; NRP, Neonatal Resuscitation Program; PALS, Pediatric Advanced Life Support; SaMD, Software as a Medical Device; VR, Virtual Reality.

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electronic health record (EHR) flowsheet with a string type). String data might contain non-numeric characters, be expressed in percentage or decimal form, and be unconstrained by maximum and minimum values. Almost 80 % of EHR data is unstructured (e.g., patient notes), which complicates data use.[4] Alternatively, laboratory data, regulated by the Clinical Laboratory Improvement Amendments of 1988, contains specific elements, including test name, resulting value, acquisition time, specimen type, and reference range.[5] Some resuscitation data comprise media files, including scanned paper code records, radiology images and videos of resuscitations.[6]

Elements of effective design

The Nielsen ten usability heuristics, rules of thumb, applied to the EHRs, resuscitation devices, and databases can facilitate data integrity and interaction (Table 1).[7] Structured evaluations with as few as 5 users can find 85 % of usability issues.[8] For example, nursing surveys improved the EHR code module at Massachusetts General Hospital.[9]

Artificial intelligence overview and fundamentals

AI encompasses machines and computers that think and act like humans, performing human tasks such as speech recognition, visual perception, language translation, and decision-making.[10] Available data and information, previously static in books and papers, is now interactive, mobile, "at your fingertips" and accessible anytime.[11] With improved capabilities and the availability of advanced informatics and AI tools, our ability to provide effective neonatal resuscitation care and education will mature. Table 2 describes various AI methodologies in the context of neonatal resuscitation.

Supervised machine learning

In supervised learning, models are trained using labeled data. For example, a cardiac arrest prediction model for hospitalized infants is trained on a comprehensive data set including important variables and a labeled outcome of cardiac arrest (Yes/No). When applied to new data, this model predicts infants who might develop cardiac arrest. Automated identification of lesions on X-rays/MRIs (classification) and predicting sepsis based on sepsis risk score (regression) are examples of supervised learning.

Unsupervised machine learning (ML)

In contrast, unsupervised learning uses unlabeled data. The model identifies data patterns and creates groups or clusters (clustering). Unsupervised ML methods have been studied to identify patterns and predict outcomes in resuscitation, including neurological recovery in out-of-hospital adult cardiac arrest.[12] In neonatal resuscitation, identifying infant phenotypes from an unlabeled dataset using variables like hemodynamic data and clinical diagnoses could help predict future events and allocate resources effectively.

Deep learning (DL)

DL uses neural networks to model the human brain functions to process and analyze large complex data sets, identify important variables, and create patterns for decision-making. DL can analyze vast amounts of complex clinical resuscitation data to identify trends and predict outcomes. DL models can predict critical events such as in-hospital code blue events.[13] Convolutional Neural Networks, an example of DL, are extensively studied for medical image analysis.[14]

Generative AI

Generative AI technology can be "prompted" using natural language to generate content text, images, video, and audio. Recently, large language models (LLMs) have ushered in a new era of information retrieval, moving from a "search era" to a "query, conversational, and digital assistant era." In November 2022, OpenAI formally released a chatbot, ChatGPT, that enables users to converse in a natural language with a reasoning engine.[15] LLM use in healthcare will range broadly from medical education and clinical care to healthcare operations.[16]

Informatics and AI in NICU resuscitation

Clinical deterioration prediction

Continuous monitoring of NICU infants generates vast cardiorespiratory data, including heart rate and rhythm, respiratory rate, blood pressure, and oxygen saturation. In most healthcare systems, these data are not continuously captured and analyzed, a missed opportunity to better understand and appreciate a patient's physiological condition. Subtle changes in newborn heart rate variability, often imperceptible to bedside clinicians, can indicate pathological conditions like early sepsis and predict mortality and other acute morbidities.[17] AI-based tools can detect these changes, promptly alert clinicians, and enable more effective and timely assessment and intervention. The HeRO® monitoring system was the first NICU-focused AI risk-scoring system to predict clinical deterioration (e.g., late-onset sepsis and necrotizing enterocolitis) based on heart rate variability trends.[18]

Several AI-enabled software platforms analyze real-time, continuous physiologic data from cardiorespiratory monitors (e.g., Etiometry®, Sickbay®). These platforms use ML techniques to provide clinical decision support (CDS). Novel models utilizing these data such as the Hyperlactatemia Index significantly predicted elevated lactate and risk of low cardiac output in pediatric critical care patients.[19]

Table 1
Nielsen's usability heuristics applied to electronic health record resuscitation interfaces.

Heuristic	Example
System status visibility	The resuscitation record screen appears different than other types of data entry. It is clear when documentation is complete.
Match between the system and the real world	Only available medications are listed as options.
User control and freedom	The process to edit / addend data is straightforward and easily recognizable.
Consistency and standards	Data definitions and terminology are standard to neonatal and pediatric resuscitation guidelines.
Error prevention	Speed buttons with standard medication concentrations and doses provide visual feedback for usual doses and complete documentation with a single touch.
Recognition rather than recall	Team actions usually occurring in sequence are listed in that order.
Flexibility and efficiency of use	End user customization is possible. A streamlined mobile option is available.
Aesthetic and minimalist design	Screens do not require scrolling. When appropriate data is presented in tables and graphs.
Helps users recognize, diagnose, and recover from errors	Users should be able to free text when the correct data is not easily entered to avoid timely loss of data.
Help and documentation	Links are provided to resuscitation guideline flowcharts.

Table 2
Artificial intelligence methodologies and applications applied to neonatal resuscitation.

AI methodology	Tasks	Labeled outcomes	Examples	Advantages	Limitations
Supervised learning	Classification (Target variable: categorical)	Yes	Prediction of cardiac arrest (Yes/No)	High accuracy with sufficient labelled data, well understood and interpretable models	Requires large, labeled datasets, Time consuming and expensive to label data, Prone to bias if data is not representative
	Regression (Target variable: continuous)	Yes	Predicting duration of ventilation in infants who had cardiac arrest		
Unsupervised learning	Clustering	No	Phenotypes of infants who had cardiac arrest	Can discover hidden patterns No need for labeled data Useful for exploratory data analysis	Difficult to interpret results May find irrelevant or spurious patterns
Deep learning	Analyzing large amounts of data and automatic feature extraction	Yes	Analysis of video data of neonatal resuscitation and identifying effective versus ineffective chest compressions	High accuracy, especially with large data sets Ability to learn complex representation	Requires large dataset and computational power Lack of interpretability (black box models)
Generative artificial intelligence Large language models	Text summarization Speech to text translation Text to video Text to audio	Yes	Resuscitation event summarization Creation of mock scenarios Mock code video assessments	Powerful for understanding and generating human languageUseful for analyzing unstructured clinical and text data	Potential for generating biased or incorrect information Difficult to interpret or explain outputs

Resuscitation documentation

Every resuscitation event (e.g., monitor data, team action, or patient assessment) has three elements: event type, details, and timing. Four types of errors occur during event documentation: omission (omitting an event that happened), commission (falsely recorded event), specification (correct event with wrong specific details), and timing.[20] Recorded events are simple to evaluate for commission errors. However, the absence of an event could represent a true event absence or an omission error. For example, electronic trauma records performed the same or better than paper documentation except for documentation that no fluids were given before arrival.[21] Specific questions on a paper code record cue the recorder to complete documentation, a visual prompt that may be missing from electronic interfaces. Post-event corrections improve accuracy, and when available, comparison to a video gold standard with feedback helps evaluate for errors.[22]

Accurate capture of exact times for events is crucial for learning. "When does a chest compression round start and stop?" Relative ordering of adjacent events or referential time (time from another event) is employed when actual time is uncertain. "Intubation occurred before chest compressions." "Two minutes of chest compressions were performed." The experienced recorder is uniquely positioned to act as a time coach and improve team performance if time documentation is accurate.[23] Electronic interfaces built for time-stamped event recording may not easily accommodate time-related uncertainty. As Neonatal Resuscitation Program (NRP) and Pediatric Advanced Life Support (PALS) differ, explicit documentation of which guideline is used is needed.

While physiologic monitor data, if artifact-free, may be directly imported, team actions and patient assessments require manual input, leaving data gaps and inconsistencies. NRP recommends recorders only document, but in practice, they often perform several tasks.[24] Environmental conditions such as loud spaces and physical distance from resuscitative events can prevent the recorder from fully observing and accurately recording an event. Recorder interviews can reveal how workflow impacts documentation quality.[22,25]

Although most level 4 NICUs document resuscitation in real-time, only 30 % use electronic documentation.[26] When implementing electronic trauma records, Nationwide Children's used recorder feedback and usability testing to improve the interface and develop recorder education and check-off.[27] Mobility advantages during documentation have led to tablet-based interfaces. Some are secondary interfaces for the main EHR, while other software is stand-alone, resuscitation documentation focused.[23,28] Enabling several observers to use multiple interfaces from different vantage points simultaneously could improve data entry.

Resuscitation management

AI-based automated cardiac rhythm analysis can support real-time decisions during resuscitation, guiding treatment based on specific cardiac arrest rhythm patterns. A classifier algorithm trained on a 273 cardiac arrest rhythm patterns dataset differentiated shockable and non-shockable rhythms with >90 % sensitivity.[29,30] Zoll Pediatric One Step™ defibrillator pads capture chest compression data, but some NICU patients are too small. These pads offer on-device feedback on chest compression quality, which can enhance performance in pediatric and neonatal resuscitations.[31] Augmented reality (AR) can place this information in the compressor's line of vision.[32] In low-resource settings, monitoring accelerometer data from the compressor's wrist was feasible for one-hand compressions.[33] Future wearables, such as gloves, may enable compression data availability for smaller neonates, including preterm infants.

Often, critically ill patients must leave the NICU and travel to the operating room or radiology suite and not uncommonly experience undesirable off-unit resuscitations. By combining multiple patient data streams from smart devices, wearables, and implantable sensors with predictive analytics, patient deterioration could be detected earlier and provide real-time CDS and post-operative monitoring beyond the NICU.[34]

Debriefing and performance evaluation

After resuscitation, accurate documentation can trigger CDS order sets for post-resuscitative care. Additionally, pediatric CDS systems that notify organ procurement organizations of impending brain death increased procurement.[35] Objective data can also inform team feedback and improve subsequent performance. The CODE ACES study used Get with the Guidelines Resusitation GWTG-R metrics, Zoll R® series accelerometer data, bedside monitor waveforms, and specialty software to create immediate visual feedback and facilitate post-event debriefing, leading to improved compliance with the PALS guideline for chest compressions in infants.[31]

Resuscitation databases

Most resuscitation data is stored locally in the EHR, data warehouses, scanned paper code records, research databases, and separate formal case review and debriefing datasets. Combining multiple data sources requires clear definitions and structure to preserve integrity and interpretability. The Utstein Style guide, a standard reporting framework for in-hospital resuscitation events, facilitates consistent collection, reporting, and benchmarking across facilities.[36] Only 9 % of United States level 4 children's hospital NICUs contribute to registries with detailed NICU resuscitation data such as the Utstein Style based American Heart Association's GWTG-R database, therefore, analysis of NICU resuscitation metrics quality and documentation completeness is not possible.[26,37] Barriers include membership costs and validated data abstraction, legal implications of shared data, and the need to contribute data for all cases. EHR-integrated registries would simplify participation.[38]

Resuscitation education and simulation

Virtual reality (VR), augmented reality (AR) and gamification

Neonatal resuscitation education enhances technical proficiency and teamwork among healthcare providers. Traditionally practiced with real-world elements like manikins, it has evolved with computer technology to include virtual and blended scenarios. Fig. 1 shows the reality-virtual continuum in neonatal resuscitation scenarios, illustrating a shift towards immersive technology in resuscitation training.[39]

NRP requires continual practice through simulation to prevent rapid loss of resuscitation skills.[40] An alternative to labor-intensive mock codes to improve neonatal resuscitation skills is serious games (e.g., board and computer games), including RETAIN (REsuscitationTrAINing for health professionals), the Neonatology Game, and DIANA (digital game-based learning).[41,42] While gamification holds promise, VR games could cause higher participant anxiety compared to high-fidelity simulation with a manikin.[43] Currently, neonatal resuscitation manikins, like NeoNatalie™, offer personalized learning experiences through AI analysis.[44] They provide real-time feedback on bag-mask ventilation. With autonomous operation, learners practice independently and obtain feedback on specific areas for improvement. Further VR advances with lifelike scenarios will boost engagement, knowledge retention, and skill acquisition. Remote coaching through simulated neonatal resuscitation significantly improves care.[45] Telesimulation provides access to high quality resuscitation training to even remote areas in low-resource settings and tracks learners' progress over time.

AI in resuscitation education

Combining AR, VR, and generative AI can enhance "on demand," individualized education. Simulations for team training on crew resource management and communication will become more robust.[46] Early examples of VR and AI in staff training for sepsis care using AI medical team members can be applied to resuscitation training.[47] Elements, including verbal and non-verbal communication skills, could be advanced by combining AR and generative AI to provide cues in a trainees' visual field during exercises.

AI could improve neonatal resuscitation and education by providing multilingual educational resources, facilitating simulation-based training, and supporting clinical decision-making. LLMs can be integrated into training programs to offer personalized learning experiences and enhance clinical skills.[48] LLM use in medical education has many advantages for trainees amidst demanding training schedule challenges, which include information overload, significant time constraints, and a lack of medical educator time and abilities.[49] Hypothesis-driven research is required to determine the most effective and favorable learning approaches for individuals and teams using AI, VR, and AR.[50]

Promoting health equity in low resource settings

Technology could transform neonatal resuscitation in low-resource healthcare settings. For example, VR simulations and e-learning proved equally effective in maintaining neonatal resuscitation skills among healthcare providers in Kenya and Nigeria.[51] Similarly, smartphone applications can create real-time decision support systems. NeoTap, a smartphone application, accurately records newborn heart rates from a finger tap, replacing the need for an electronic monitor.[52]

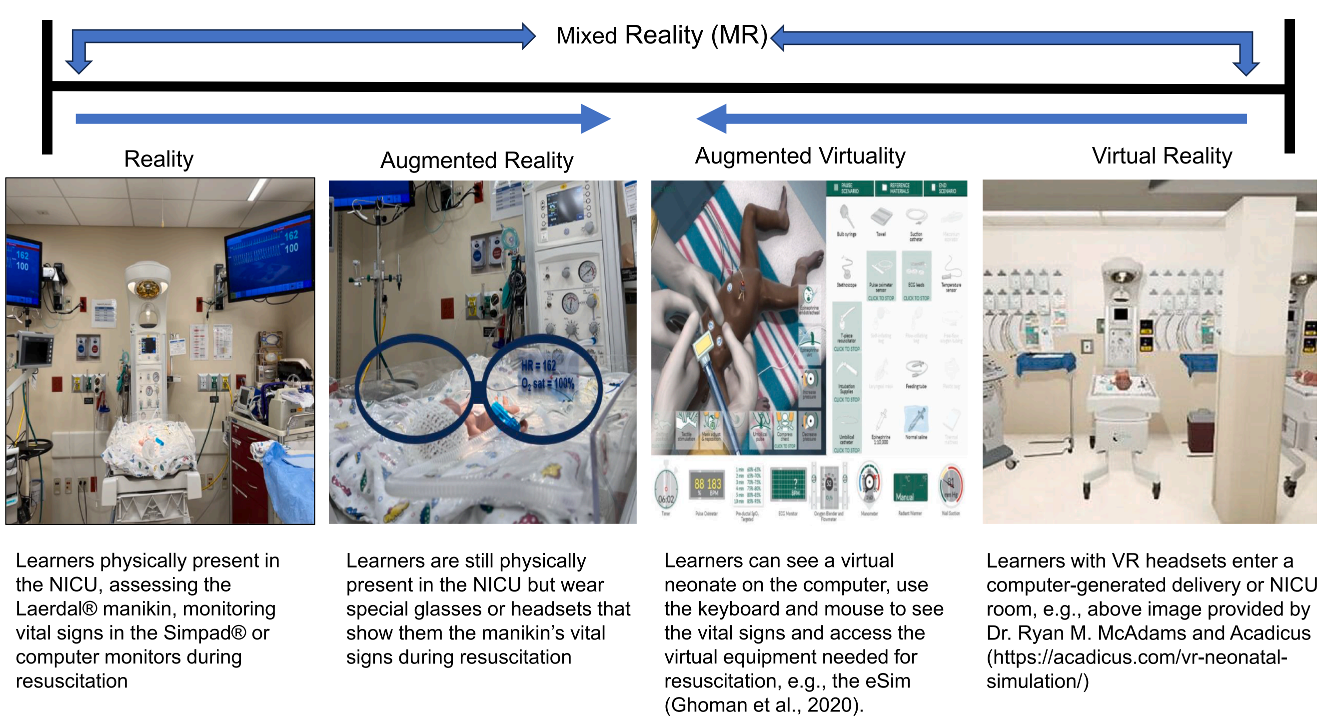

Fig. 1. Milgram and Kishino's reality-virtuality continuum with neonatal resuscitation examples.[39]

AI-based object detection in video clips of neonatal and infant resuscitation could provide insights into the effectiveness of various resuscitation techniques based on resource availability and identify areas for improvement.[53] AI models can analyze and monitor data to provide recommendations, such as when to start chest compressions or administer medications, particularly in areas with limited skilled clinicians for neonatal resuscitation.

Legal and ethical concerns

Data privacy and security

Healthcare AI model development and data storage are challenged by the sensitive nature of personal healthcare data and concern for violating privacy laws such as the Health Insurance Portability and Accountability Act of 1996 (HIPAA) and the European Union's General Data Protection Regulation (GDPR). Inappropriate access, data breaches, and inference attacks that identify private information from de-identified data can result in serious privacy violations. Nonetheless, AI advances in healthcare will be made by leveraging large amounts of existing data in EHRs. Techniques like differential privacy (adding noise to the data queries) and federated learning (models are trained locally at the data source, and insights are shared centrally without sharing the raw data) can help address data security and privacy issues.[54]

Bias and discrimination

Significant bias exists in pediatric healthcare data.[55] When biased data is used to train AI models, incorrect output can lead to misguided or incorrect healthcare decisions. A commercially available, routinely used AI algorithm falsely assigned Black patients to lower risk categories for the same level of pathology compared to White patients because the model used healthcare expenditure as a proxy for severity.[56] If AI is to benefit all, datasets need to include diverse populations. To facilitate this, one AI expert panel strongly recommends an opt-out approach for the inclusion of patient data along with consent when developing AI models.[57] Further, healthcare systems should adopt ethical frameworks when considering AI models in clinical settings to prevent bias and promote fairness. A recently proposed ethical framework for using and evaluating AI-based models, particularly in pediatrics, considers truth, goodness, and wisdom as important components.[58]

Accountability and liability

The laws addressing AI-enabled recommendations and liability are still evolving and in their infancy. The liability aspects of using AI in clinical care are hotly debated. In the future, we might see a shared liability responsibility between clinicians and technology companies when using AI in healthcare. Hence, clinicians must actively evaluate, implement, and supervise AI tools in clinical decision-making. In 2019, the Food and Drug Administration published guidance papers to facilitate a safe rollout of AI-ML-enabled software and medical devices (SaMD) in healthcare. These included a regulatory framework, an action plan named "AI/ML SaMD Action Plan," and, most recently, updates on the collaboration between medical product centers.[59] The regulatory framework and action plan highlight the need for quality systems to incorporate good ML practices, a risk-based approach to premarket submissions, and monitoring these devices' real-world performance.

Emerging technologies and innovations

Digital twin

When provided with real-time data, a digital twin replicates a real scenario in a virtual world and applies ML algorithms. A digital twin approach improves medical education by testing and training *in silico* with a risk-free, simulated environment based on actual events and data. This approach in critical care education has demonstrated favorable usability and acceptance by trainees.[60] Another novel approach with digital twins is the creation and use of synthetic data, which allows for realistic data and, importantly, protects privacy.[61]

Computer vision

Computer vision, a field within AI, extracts meaningful information from digital images and videos. Building on the extensive use in self-driving cars, computer vision could improve neonatal resuscitation by enhancing resuscitation techniques, automating processes, creating better monitoring and alert systems, and performing post-event analyses. In early studies, visual sensors detected very preterm infants' heart and respiratory rates without adherent sensors.[62] In the future, it may be possible to continuously monitor patient color, chest movements, and team member actions during resuscitations. By analyzing video feeds in real-time, computer vision could detect deviations from expected patterns (like inadequate chest rise or cyanosis) and alert medical staff.[63]

Gaps and future opportunities

Table 3 outlines specific targets to improve informatics and AI support for neonatal resuscitation and provides actionable suggestions.

Table 3
Domains, gaps, and opportunities for informatics and AI in neonatal resuscitation.

Domain / Gap	Opportunity
Valid Data Acquisition: Lack of informatics tools to accurately capture resuscitation data	NICU clinicians, informaticists, and researchers should collaborate with EHR vendors to validate interfaces and standardize recorder training for accurate documentation of resuscitation events. Real-time data should be recorded in industry-consistent structured formats with clear definitions.
Data Aggregation: Lack of large datasets involving diverse patient population	Enabling broad participation in CPR registries for NICU patients should be a priority.
New Devices: Lack of devices capable of monitoring chest compression quality for all neonates	Devices capable of assessing chest compression effectiveness in premature neonates and for use in low-resource settings, are needed.
AI and Informatics Education: Lack of awareness and integration of AI and informatics tools	AI integration in NICU resuscitation education could improve long-term skill retention. Awareness and education about AI and informatics tools for NICU clinicians is vital.
Bias Oversight: Bias in healthcare datasets that could cause equity and fairness issues in AI models	When deploying AI applications in pediatric and neonatal healthcare, data bias must be evaluated rigorously along with the use of ethical frameworks.
Equity: Lack of skilled clinicians in low-resource settings	AI could significantly improve staff abilities and patient outcomes for neonatal resuscitation in low-resource settings.

AI: Artificial Intelligence; EHR: Electronic Health Record; CPR: Cardiopulmonary Resuscitation; NICU: Neonatal Intensive Care Unit;.

Conclusions

NICU resuscitation care is constantly evolving. It's important to focus on accurate data collection and aggregation through informatics tools to support this progress. Advances in informatics and AI can help by emphasizing best practices for correct and complete data collection and developing prediction models for enhanced resuscitation team performance. Additionally, explicit focus on innovation in medical devices for data acquisition in all patients, including low-resource settings and bias elimination, are the next steps towards equitable care. Integrating informatics with AI's safe and ethical adoption will be key to advancing neonatal resuscitative care. NICU clinicians must understand these new technologies to ensure appropriate implementation and participate in the technology evaluation and development. Only then will the promise of improved patient care, specifically neonatal resuscitation, be realized.

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