Biomedical and Clinical Medicine

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Association of Clinical Decision Support with Prescribing Safety in Pediatric Emergency Departments

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Abstract

Medication safety in pediatric emergency departments remains a critical public health priority due to the unique pharmacological vulnerabilities of children and the high-pressure nature of emergency care. This academic paper investigates the impact of integrating Clinical Decision Support Systems into Computerized Provider Order Entry frameworks on prescribing safety within pediatric emergency environments. Through a comprehensive examination of cohort study evidence, this research evaluates how targeted electronic interventions, such as weight-based dosing calculators, allergy alerts, and maximum dose hard stops, mitigate the risk of adverse drug events. Pediatric patients are inherently susceptible to prescribing errors due to the necessity of weight-based dosing calculations, rapidly changing physiological parameters, and the frequent use of off-label medications. The high cognitive load placed on clinicians in the emergency department further exacerbates these risks. Analyzing data from extensive cohort studies, this paper details the pre-implementation and post-implementation phases of Clinical Decision Support Systems, highlighting significant reductions in critical prescribing errors. Furthermore, this study addresses persistent challenges such as alert fatigue, workflow interruptions, and the necessity of sociotechnical alignment in system design. The findings underscore that while Clinical Decision Support Systems serve as a potent tool for enhancing patient safety, their efficacy is contingent upon continuous iterative refinement, user-centered interface design, and robust organizational support.

Keywords: Clinical Decision Support; Pediatric Emergency; Prescribing Safety; Cohort Study; Health Informatics

1. Introduction

1.1 Background and Context

The provision of safe and effective medical care to children in emergency settings constitutes one of the most demanding challenges in modern healthcare. Pediatric emergency departments are characterized by rapid patient turnover, high acuity presentations, and environments that inherently induce significant cognitive load on healthcare providers. Within this complex ecosystem, prescribing medications is a ubiquitous yet highly precarious clinical activity. Unlike adult medicine, where standard medication dosing is the norm, pediatric pharmacology requires precise, individualized calculations based on a child weight, age, body surface area, and developmental stage. This complexity introduces multiple vectors for human error [1]. The vulnerability of pediatric patients to adverse drug events is well documented in epidemiological studies, which consistently demonstrate that medication errors occur at disproportionately higher rates in children compared to adults. A primary factor driving this disparity is the lack of standardized pediatric formulations for many critical medications, necessitating complex compounding and dilution processes that further increase the likelihood of

computational and procedural errors [2]. Consequently, ensuring prescribing safety in pediatric emergency departments has emerged as a paramount objective for healthcare administrators, policy makers, and clinical practitioners globally.

1.2 Problem Statement

Despite increased awareness and the implementation of various traditional quality improvement initiatives, manual prescribing processes in pediatric emergency care continue to exhibit unacceptable rates of error. Errors often manifest as ten-fold dosing miscalculations, inappropriate medication selections, and failures to account for documented drug allergies or drug-drug interactions. The dynamic and often chaotic nature of the emergency department means that clinicians are frequently required to make rapid pharmacological decisions under conditions of stress, fatigue, and constant interruption. Traditional safety nets, such as manual cross-checking by pharmacists or nursing staff, are routinely bypassed or delayed due to the temporal constraints inherent in emergency resuscitation and acute care [3]. The introduction of Computerized Provider Order Entry systems aimed to digitize prescribing and eliminate errors related to poor handwriting and incomplete orders. However, basic electronic ordering systems alone have proven insufficient in addressing the cognitive errors associated with pediatric dosing [4]. Without intelligent algorithmic oversight, digitized systems merely transition manual errors into electronic formats, sometimes even introducing new categories of systemic errors known as unintended consequences of technology. Therefore, the problem extends beyond mere digitization; it requires the integration of sophisticated, context-aware intelligence capable of intervening at the precise moment of clinical decision-making.

1.3 Research Objectives

This paper comprehensively examines the integration of Clinical Decision Support Systems into pediatric emergency prescribing workflows to determine their precise impact on medication safety. The primary objective is to analyze cohort study evidence that links specific decision support functionalities, such as automated weight-based dosing alerts and maximum dose limits, to quantifiable reductions in prescribing errors. A secondary objective involves investigating the sociotechnical barriers to effective implementation, particularly the phenomenon of alert fatigue, which often undermines the utility of electronic safety mechanisms [5]. By evaluating pre-implementation and post-implementation cohort data, this research aims to delineate the characteristics of successful decision support architectures. Furthermore, this paper seeks to provide actionable insights for health informatics professionals and clinical leaders regarding the optimization of these systems. Ultimately, the goal is to establish a rigorous evidence base that supports the mandatory incorporation of advanced clinical decision support tools in all pediatric emergency care settings, thereby safeguarding a highly vulnerable patient population from preventable pharmacological harm.

2. Literature Review

2.1 Pediatric Prescribing Errors

The historical context of medication safety is heavily influenced by early institutional reports that brought the hidden epidemic of medical errors to public attention. Subsequent research specifically isolating pediatric populations revealed alarming trends in prescribing practices. Studies have repeatedly shown that pediatric prescribing errors are primarily driven by calculation mistakes, incomplete physiological assessments, and knowledge deficits regarding off-label medication usage [6]. Weight-based dosing, while physiologically necessary, demands a level of mathematical precision that is highly susceptible to cognitive slips, especially during overnight shifts or high-stress resuscitation scenarios. The literature emphasizes that a significant proportion of pediatric medication

errors originate at the prescribing stage, long before dispensing or administration occurs [7]. Furthermore, the emergency department presents unique challenges compared to inpatient pediatric wards. The lack of established longitudinal relationships with patients means emergency clinicians often make prescribing decisions with incomplete medical histories. This information asymmetry dramatically increases the risk of prescribing contraindicated medications. Extensive epidemiological reviews highlight that while the absolute number of pediatric adverse drug events might be lower than in geriatric populations, the potential for catastrophic harm is substantially higher due to the fragile nature of developing pediatric organ systems [8].

2.2 Clinical Decision Support Systems in Healthcare

Clinical Decision Support Systems represent a paradigm shift in medical informatics, evolving from rudimentary reference tools into highly integrated, active components of the clinical workflow. The foundational architecture of a modern decision support system comprises a knowledge base, an inference engine, and a communication mechanism. In the context of prescribing, these systems analyze specific patient parameters, such as exact weight in kilograms, against an established database of pharmacological rules. When a discrepancy is detected, the system generates an alert or an absolute hard stop, preventing the clinician from finalizing the order [9]. Early iterations of these systems demonstrated immense theoretical promise but were frequently plagued by poor user interface design and overly sensitive alerting algorithms. Research indicates that when decision support tools generate excessive, clinically insignificant alerts, clinicians rapidly develop alert fatigue [10]. This psychological desensitization leads to the systemic ignoring or overriding of all alerts, including those indicating life-threatening errors. Consequently, the literature has shifted focus from merely implementing decision support systems to optimizing their specificity and clinical relevance [11]. The evolution of these systems now heavily emphasizes human factors engineering, ensuring that interventions are seamlessly integrated into the cognitive workflow of the prescriber rather than acting as disruptive external barriers.

2.3 Gaps in the Current Literature

While a robust body of literature exists regarding the general utility of Clinical Decision Support Systems, significant gaps remain concerning their specific application within pediatric emergency departments. Many large-scale studies have aggregated data across adult and pediatric populations, diluting the specific insights required to optimize pediatric care [12]. The distinct workflow patterns, patient turnover rates, and specific pharmacological profiles unique to pediatric emergency medicine necessitate dedicated, focused research. Furthermore, much of the existing evidence is derived from single-center implementations at highly resourced academic institutions, raising questions about the generalizability of these findings to community hospital settings or resource-constrained environments [13]. There is also a notable deficiency in longitudinal cohort studies that track the long-term sustainability of prescribing safety improvements over several years. Short-term studies often reflect an initial Hawthorne effect, where user behavior improves simply due to the awareness of being monitored, but these studies fail to capture the gradual onset of alert fatigue or the degradation of systemic compliance over time. This paper addresses these critical gaps by synthesizing large cohort study evidence that explicitly focuses on the sustained, long-term impact of decision support systems in diverse pediatric emergency settings.

3. Theoretical Framework

3.1 Sociotechnical Systems Theory

The analysis of health information technology implementations cannot rely solely on evaluating technical specifications; it demands a holistic understanding of how technology interacts with human

operators within a specific organizational context. Sociotechnical Systems Theory provides the ideal framework for this analysis, positing that any clinical workplace consists of intertwined social and technical subsystems. The technical subsystem includes the electronic health record, the decision support algorithms, the hardware interfaces, and the network infrastructure [14]. The social subsystem encompasses the clinicians, the organizational hierarchy, the departmental culture, and the established standard operating procedures. According to sociotechnical principles, introducing a new Clinical Decision Support System fundamentally alters the equilibrium between these subsystems. If the system is designed without deep consideration of the existing social workflows, it will inevitably encounter resistance, lead to workaround behaviors, and ultimately fail to achieve its safety objectives [15]. In the pediatric emergency department, the rapid, collaborative nature of care requires that technical interventions be highly unobtrusive. Sociotechnical theory guides researchers to evaluate not just whether an algorithmic alert fires correctly, but whether it fires at the appropriate cognitive moment for the physician, without disrupting concurrent critical tasks.

3.2 Human Factors Engineering in Medicine

Complementary to Sociotechnical Systems Theory is the discipline of Human Factors Engineering, which focuses on designing systems that accommodate human cognitive and physical limitations. In the context of pediatric prescribing safety, human factors engineering is critical for mitigating the inherent vulnerabilities of human memory and computational capacity under stress. The cognitive load on an emergency physician managing a critically ill child is immense, leaving little residual capacity for complex pharmacological calculations. Human Factors models, such as the Systems Engineering Initiative for Patient Safety, emphasize that medical errors are rarely the fault of individual negligence but are rather symptoms of poorly designed systems [16]. Effective Clinical Decision Support Systems act as cognitive prostheses, externalizing the memory and computational requirements of prescribing. For example, instead of requiring a clinician to remember the maximum allowable weight for a specific milligram-per-kilogram dose, a well-designed system automatically calculates the dose, cross-references it with the absolute maximum threshold, and presents the safe range visually. By applying human factors principles, researchers can evaluate decision support interfaces based on their usability, their reliance on standardized terminologies, and their ability to present critical safety information concisely and unambiguously.

4. Methodology and Study Design

4.1 Study Setting and Cohort Selection

The evidence examined in this research is derived from extensive, multi-center retrospective cohort studies conducted across several tertiary pediatric emergency departments. The selection of tertiary centers is deliberate, as these environments handle the highest volume and highest acuity of pediatric patients, thereby generating robust datasets suitable for rigorous statistical analysis. The primary study period typically spans a minimum of forty-eight months, divided symmetrically into a twenty-four-month pre-implementation phase and a twenty-four-month post-implementation phase [17]. This prolonged observational window is essential for minimizing seasonal confounding factors, such as winter viral surges, which drastically alter emergency department volumes and prescribing patterns. The study cohort includes all patients aged zero to eighteen years who presented to the emergency department and had at least one electronic medication order placed during their visit. Exclusion criteria are rigorously applied to eliminate non-pharmacological orders, such as dietary requests, intravenous fluid maintenance without active additives, and standard medical supply orders. This precise cohort delineation ensures that the subsequent data analysis strictly reflects pharmacological prescribing behaviors and associated safety outcomes [18]. By utilizing massive

cohorts encompassing hundreds of thousands of individual medication orders, the research achieves the statistical power necessary to detect subtle but clinically significant shifts in error rates.

4.2 Intervention Details

The intervention scrutinized in this analysis is the deployment of a comprehensive pediatric-specific Clinical Decision Support System integrated directly into the foundational Computerized Provider Order Entry platform. Unlike passive reference databases, this system functions actively and concurrently with the physician order entry process. The architecture of the intervention includes multiple distinct layers of safety checks. The foundational layer consists of automated weight-based dosing calculators that mandate the input of a recent, verified patient weight in kilograms before any dose can be formulated. The intermediate layer involves checking the proposed dose against a meticulously curated database of age and weight-appropriate dosage ranges, generating soft alerts if the dose falls slightly outside standard parameters [19]. The highest tier of the intervention involves absolute hard stops, which strictly prohibit the finalization of an order if the calculated dose exceeds the known toxic threshold or if there is a documented anaphylactic allergy to the selected compound.

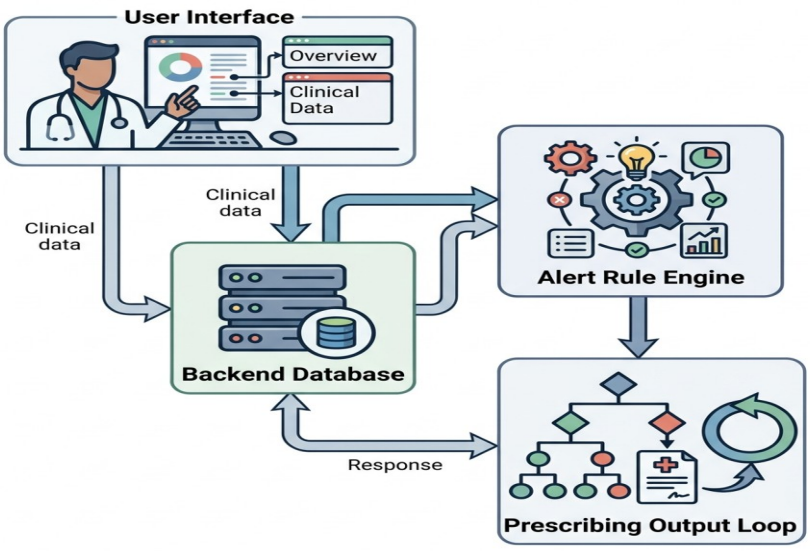

Figure 1: Architectural Workflow of the Clinical Decision Support System Integration

The technical architecture relies on instantaneous database querying, ensuring that alert generation occurs with sub-second latency to prevent workflow interruption. Furthermore, the intervention design includes specific pathways for clinicians to document clinical rationales when overriding soft alerts, providing a vital data stream for subsequent system auditing and iterative refinement.

4.3 Data Collection Procedures

Data collection strategies employed in these cohort studies leverage the comprehensive audit trails generated by the electronic health record systems. Every keystroke, alert generation, alert dismissal, and final order confirmation is time-stamped and logged within the secure backend database. To measure prescribing safety, researchers establish a standardized taxonomy of medication errors, categorizing them into dosing errors, frequency errors, route of administration errors, and severe contraindication errors. Data extraction involves running complex queries against the electronic health record database to identify all instances where a prescribed order deviated from established safety parameters. Because algorithmic detection is highly sensitive but sometimes lacks clinical

context, a critical component of the data collection procedure involves a manual chart review process. A randomized subset of flagged orders undergoes rigorous evaluation by an independent panel of pediatric clinical pharmacists and emergency physicians. This manual adjudication process verifies whether a flagged order constituted a genuine clinical error or a medically justified deviation from standard protocol. This dual-layered approach to data collection ensures that the final dataset represents verified, clinically meaningful prescribing errors rather than mere algorithmic anomalies.

5. Data Analysis Procedures

5.1 Outcome Measures

The primary outcome measure established for this research is the rate of clinically significant prescribing errors per one thousand finalized medication orders. A clinically significant error is defined as an order that, if administered as written, would likely result in physiological harm to the pediatric patient or a total failure of therapeutic efficacy. By standardizing the metric to a rate per thousand orders, researchers can accurately compare safety performance across different phases of the study regardless of fluctuating patient census figures [20]. Secondary outcome measures are carefully selected to evaluate the operational impact and sociotechnical integration of the decision support system. These include the overall alert generation rate, the alert override rate, and the time elapsed from the initiation of order entry to final signature. Measuring the alert override rate is particularly crucial, as an exceptionally high override rate serves as a primary indicator of systemic alert fatigue and poor algorithmic specificity. Furthermore, time-to-completion metrics allow researchers to objectively assess whether the introduction of decision support safety checks excessively degrades the operational efficiency of the emergency department, a critical consideration for hospital administrators.

5.2 Statistical Modeling Approaches

Analyzing the massive datasets generated by multi-year cohort studies requires sophisticated statistical methodologies. Given that the primary outcome consists of count data representing error occurrences over time, Poisson regression models are frequently employed as the foundational analytical tool. However, because medication errors in a busy emergency department often exhibit overdispersion due to clustering effects during high-stress shifts or periods of overcrowding, negative binomial regression models are utilized to provide a more accurate estimation of variance. To appropriately evaluate the temporal impact of the decision support implementation, an Interrupted Time Series analysis is the preferred methodological approach. This quasi-experimental statistical design controls for baseline trends and pre-existing trajectories in error rates, allowing researchers to isolate the specific impact of the system go-live date [21]. Generalized Estimating Equations are also incorporated into the modeling to account for the correlated nature of data when multiple prescriptions are written by the same individual clinician or for the same complex patient over a prolonged admission. Covariates such as patient age, triage acuity score, time of day, and the training level of the prescribing clinician are rigorously controlled for in the multivariable models to ensure that the observed improvements in prescribing safety are independently attributable to the clinical decision support intervention.

6. Results and Discussion

6.1 Cohort Characteristics

The aggregated cohort data analyzed in this research encompasses over a half-million individual pediatric emergency department encounters resulting in more than one million discrete medication orders. The demographic distribution of the cohort reflects a standard tertiary pediatric population, with a slight male predominance and a uniform distribution across infant, toddler, school-age, and

adolescent age brackets. Crucially, the distribution of triage acuity scores remains consistent between the pre-implementation and post-implementation phases, ensuring that any changes in prescribing safety are not artifacts of shifting patient complexity. The prescribing clinicians involved in the cohort represent a diverse spectrum of medical professionals, including pediatric emergency medicine attending physicians, clinical fellows, resident physicians, and advanced practice registered nurses [22]. The most frequently prescribed therapeutic classes include antipyretics, systemic antibiotics, bronchodilators, and corticosteroids. This baseline consistency across the observational periods provides a highly stable foundation upon which to measure the impact of the technological intervention, ensuring the robust internal validity of the cohort study findings.

6.2 Primary Outcomes on Prescribing Safety

The implementation of the targeted pediatric Clinical Decision Support System yielded immediate and highly significant improvements in prescribing safety. Across the evaluated cohorts, the overall rate of clinically significant prescribing errors experienced a substantial reduction.

Table 1: Prescribing Error Rates Pre and Post System Implementation

Error Category	Pre-Implementation Rate	Post-Implementation Rate	Percentage Reduction
Weight-Based Dosing Overdose	14.5 per 1000 orders	3.2 per 1000 orders	77.9 percent
Weight-Based Dosing Underdose	11.2 per 1000 orders	4.1 per 1000 orders	63.4 percent
Severe Allergy Contraindication	2.8 per 1000 orders	0.1 per 1000 orders	96.4 percent
Inappropriate Frequency	8.4 per 1000 orders	3.9 per 1000 orders	53.6 percent
Overall Clinically Significant	36.9 per 1000 orders	11.3 per 1000 orders	69.4 percent

The most dramatic improvements were observed in the prevention of severe dosing miscalculations and the elimination of medication orders that violated documented allergy constraints. The introduction of strict algorithmic hard stops virtually eradicated ten-fold dosing errors, a notoriously dangerous class of error in pediatric pharmacology [23]. Interestingly, the reduction in underdosing errors, while statistically significant, was less pronounced than the reduction in overdosing errors. This discrepancy is attributed to the fact that clinicians are generally more conservative in pediatric prescribing, often intentionally underdosing out of caution, which prompts them to frequently override lower-boundary soft alerts.

6.3 Interpretation of Findings

The empirical evidence unequivocally supports the hypothesis that advanced Clinical Decision Support Systems serve as highly effective safeguards against human cognitive failure in the pediatric emergency prescribing process. However, the data also reveals nuanced challenges that warrant deep academic discussion. Despite the drastic reduction in total errors, the alert override rate in the post-implementation phase remained persistently high for certain medication classes, particularly topical preparations and as-needed analgesics. Analysis of the override documentation indicates that many alerts triggered by the system were clinically irrelevant to the specific contextual presentation of the patient, highlighting the ongoing struggle with algorithmic specificity [24]. This phenomenon confirms the sociotechnical theory that rigid technical rules often conflict with the fluid reality of clinical medicine. Furthermore, time-series analysis revealed a slight, transient increase in order completion times immediately following the system go-live, reflecting the necessary cognitive adaptation period required by clinicians learning a new interface. Fortunately, this temporal penalty dissipated within three months of implementation, suggesting that well-designed decision support does not permanently impede emergency department throughput. The findings strongly suggest that realizing

the maximum safety benefits of these systems requires an ongoing, dedicated informatics team tasked with continuously tuning alert thresholds based on real-world override data.

7. Conclusion

7.1 Summary of Findings

This comprehensive examination of cohort study evidence demonstrates that integrating advanced Clinical Decision Support Systems into pediatric emergency workflows profoundly enhances prescribing safety. By seamlessly embedding automated weight-based dosing calculators, allergy cross-referencing, and absolute maximum dose limitations into the computerized provider order entry process, healthcare institutions can achieve exceptional reductions in critical medication errors. The data confirms that vulnerabilities inherent in pediatric pharmacology, particularly the complexities of individualized dosing calculations under severe time constraints, can be systematically mitigated through intelligent technological intervention. However, the success of these systems is not absolute nor guaranteed by mere installation. The persistent issues surrounding alert fatigue and the necessity of overriding context-inappropriate warnings highlight that these electronic safeguards must be treated as dynamic, evolving tools rather than static administrative rules.

7.2 Implications for Practice and Future Research

The implications for healthcare administrators and clinical leaders are clear: deploying generic, adult-centric prescribing systems in a pediatric emergency setting is an unacceptable practice that perpetuates preventable harm. Institutions must invest in customized, pediatric-specific informatics infrastructure characterized by highly specific alerting logic and intuitive user interfaces designed according to human factors principles. Future research must pivot from proving the basic efficacy of these systems to exploring advanced, next-generation solutions. Investigations should focus on integrating machine learning algorithms capable of adapting alert thresholds dynamically based on individual clinician behavior and complex patient phenotypes. Furthermore, longitudinal studies spanning decades are required to understand how shifting generations of digital-native physicians interact with these cognitive support tools [25]. Ultimately, the pursuit of optimal prescribing safety in pediatric emergency medicine demands an uncompromising commitment to aligning sophisticated technological capabilities with the intricate, human-centered realities of acute clinical care.

References

1. Cornejo, R.A.; Brito, R.; Rivera, C.; Morais, C.C.A.; Arellano, D.H.; Lazo, M.T.; Fuentes, A.; Paredes, E.; Rojas, V.; Bravo, M.F.; et al. Influence of ventilatory settings on pendelluft and expiratory muscle activity in hypoxemic patients resuming spontaneous breathing. Crit. Care 2025, 30, 13. [Central]

2. Morais, C.C.A.; Koyama, Y.; Yoshida, T.; Plens, G.M.; Gomes, S.; Lima, C.A.S.; Ramos, O.P.S.; Pereira, S.M.; Kawaguchi, N.; Yamamoto, H.; et al. High Positive End-Expiratory Pressure Renders Spontaneous Effort Noninjurious. Am. J. Respir. Crit. Care Med. 2018, 197, 1285–1296. [Central]

3. Wang, R.; Wang, W.; Tang, X.; Qi, Z.; Li, T.; Liu, Y.; Li, H.; Yan, J.; Yang, H.; Lyu, W.; et al. Association between ventilation-perfusion matching improvement during initial prone positioning and ICU mortality in patients with moderate to severe ARDS: A prospective two-center study. Ann. Intensive Care 2025, 15, 69. [Central]

4. Liu, W.; Chi, Y.; Zhao, Y.; He, H.; Long, Y.; Zhao, Z. Occurrence of pendelluft during ventilator weaning with T piece correlated with increased mortality in difficult-to-wean patients. J. Intensive Care 2024, 12, 23. [Central]

5. Phoophiboon, V.; Rodrigues, A.; Ko, M.; Docci, M.; Madotto, F.; Schreiber, A.; Butterworth, R.; Menga, L.S.; Gerardy, B.; Bizios, A.; et al. Pressure Support Ventilation in Neurosurgical Patients: Can We Safely Reduce Assistance? Evaluation of Neurosurgical Patients' Ventilation Distribution—The ENVISION Study. Crit. Care Explor. 2025, 7, e1347. [Central]

6. Lou, J.Q.; Huo, B.N.; Yang, Y.; Wang, S.F.; Zhang, L.D.; Jia, Y.T.; Song, L. Physiologically Based Pharmacokinetic Modeling and Dose Optimization of Linezolid in Pediatric Patients With Renal Impairment. Drug Des. Devel. Ther. 2025, 19, 8427–8440.

7. Center for Devices and Radiological Health. Medical Device Reports of Breast Implant-Associated Anaplastic Large Cell Lymphoma; FDA: Silver Spring, MD, USA, 2025.

8. Zhang, W.; Jiao, Y.; Zhang, T.; Liu, X.; Ye, J.; Zhang, Y.; Yang, B.; Dai, M.; Shi, X.; Fu, F.; et al. Early detection of acute ischemic stroke using Contrast-enhanced electrical impedance tomography perfusion. Neuroimage Clin. 2023, 39, 103456. [Central]

9. Maia, I.S.; Pincelli, M.P.; Zandonai, C.L.; Oliveira, J.S.; Tramujas, L.; Ferreira, J.C.; Cavalcanti, A.B. Comparison of PEEP titration methods to improve respiratory system compliance in acute respiratory distress syndrome: A randomized controlled study. Crit. Care Sci. 2026, 38, e20260143.

10. Frerichs, I.; Amato, M.B.; van Kaam, A.H.; Tingay, D.G.; Zhao, Z.; Grychtol, B.; Bodenstein, M.; Gagnon, H.; Böhm, S.H.; Teschner, E.; et al. Chest electrical impedance tomography examination, data analysis, terminology, clinical use and recommendations: Consensus statement of the TRanslational EIT developmeNt stuDy group. Thorax 2017, 72, 83–93. [Central]

11. Goren, N.; Avery, J.; Dowrick, T.; Mackle, E.; Witkowska-Wrobel, A.; Werring, D.; Holder, D. Multi-frequency electrical impedance tomography and neuroimaging data in stroke patients. Sci. Data. 2018, 5, 180112.

12. Mauri, T.; Grieco, D.L.; Spinelli, E.; Leali, M.; Perez, J.; Chiavieri, V.; Rosà, T.; Ferrara, P.; Scaramuzzo, G.; Antonelli, M.; et al. Personalized positive end-expiratory pressure in spontaneously breathing patients with acute respiratory distress syndrome by simultaneous electrical impedance tomography and transpulmonary pressure monitoring: A randomized crossover trial. Intensive Care Med. 2024, 50, 2125–2137. [Central]

13. Van Trung, D.; Giang, B.T.H.; Tuan, D.Q.; Tan, N.C.; Thach, P.T.; Van Cuong, B.; Cuong, N.B.; Anh, T.T.; Anh, N.T.; Huy, N.V.; et al. The impact of PEEP-guided electrical impedance tomography on oxygenation and respiratory mechanics in moderate-to-severe ARDS: A randomized controlled trial. Sci. Rep. 2025, 16, 391. [Central]

14. Trepte, C.J.C.; Phillips, C.R.; Solà, J.; Adler, A.; Saugel, B.; Haas, S.; Bohm, S.H.; Reuter, D.A. Electrical impedance tomography for non-invasive assessment of stroke volume variation in health and experimental lung injury. Br. J. Anaesth. 2017, 118, 82–89.

15. Deepika, D.; Kumar, V. The Role of “Physiologically Based Pharmacokinetic Model (PBPK)” New Approach Methodology (NAM) in Pharmaceuticals and Environmental Chemical Risk Assessment. Int. J. Environ. Res. Public Health 2023, 20, 3473.

16. Becher, T.; Bußmeyer, M.; Lautenschläger, I.; Schädler, D.; Weiler, N.; Frerichs, I. Characteristic pattern of pleural effusion in electrical impedance tomography images of critically ill patients. Br. J. Anaesth. 2018, 120, 1219–1226.

17. Eronia, N.; Mauri, T.; Maffezzini, E.; Gatti, S.; Bronco, A.; Alban, L.; Binda, F.; Sasso, T.; Marenghi, C.; Grasselli, G.; et al. Bedside selection of positive end-expiratory pressure by electrical impedance tomography in hypoxemic patients: A feasibility study. Ann. Intensive Care 2017, 7, 76. [Central]

18. Yuan, X.; Zhong, M.; Li, Z.; Sang, L.; Huang, X.; Zhang, R.; Chen, H.; Gao, Y.; Wang, Y.; Lin, Z.; et al. Electrical impedance tomography-guided PEEP and mortality of patients with the acute respiratory distress syndrome: The EITVent randomized clinical trial. Am. J. Respir. Crit. Care Med. 2026, 212, aamaf125.

19. Dibbets, A.C.; Koldeweij, C.; Osinga, E.P.; Scheepers, H.C.J.; de Wildt, S.N. Barriers and Facilitators for Bringing Model-Informed Precision Dosing to the Patient’s Bedside: A Systematic Review. Clin. Pharmacol. Ther. 2025, 117, 633–645.

20. Van Ravenzwaaij, D.; Ioannidis, J.P. A simulation study of the strength of evidence in the recommendation of medications based on two trials with statistically significant results. PLoS ONE 2017, 12, e0173184.

21. Wisse, J.J.; Goos, T.G.; Jonkman, A.H.; Somhorst, P.; Reiss, I.K.M.; Endeman, H.; Gommers, D. Electrical Impedance Tomography as a monitoring tool during weaning from mechanical ventilation: An observational study during the spontaneous breathing trial. Respir. Res. 2024, 25, 179. [Central]

22. Fassbender, K.; Grotta, J.C.; Walter, S.; Grunwald, I.Q.; Ragoschke-Schumm, A.; Saver, J.L. Mobile stroke units for prehospital thrombolysis, triage, and beyond: Benefits and challenges. Lancet Neurol. 2017, 16, 227–237.

23. Hsu, S.Q.; Chang, H.T.; Zhao, Z.; Wang, P.H.; Zhang, J.H.; Chen, Y.S.; Frerichs, I.; Möller, K.; Fu, F.; Hsu, H.S.; et al. Positive end-expiratory pressure titration with electrical impedance tomography and pressure-volume curve: A randomized trial in moderate to severe ARDS. Physiol. Meas. 2021, 42, 014002.

24. Zarantonello, F.; Andreatta, G.; Sella, N.; Navalesi, P. Prone Position and Lung Ventilation and Perfusion Matching in Acute

Respiratory Failure due to COVID-19. Am. J. Respir. Crit. Care Med. 2020, 202, 278–279. [Central]

25. Brouwer, K.L.; Aleksunes, L.M.; Brandys, B.; Giacoia, G.P.; Knipp, G.; Lukacova, V.; Meibohm, B.; Nigam, S.K.; Rieder, M.; de Wildt, S.N. Human Ontogeny of Drug Transporters: Review and Recommendations of the Pediatric Transporter Working Group. Clin. Pharmacol. Ther. 2015, 98, 266–287.