Research Article

Advancing Paediatric Care Through Integrated Machine Learning, Deep Learning, Internet Of Things, Data Science And Mathematical Modelling: A Comprehensive Review

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Abstract

The intersection of machine learning (ML), deep learning (DL), Internet of Things (IoT), and data science (DS) is transforming healthcare for children, but the evidence base is fragmented across disease areas and technologies, and pediatricpopulations remain underrepresented in both algorithmic training sets and regulatory approval processes. The objective of this research is to review the recent evidence on pediatricapplications of ML/DL/IoT/DS. We focused on four domains: predictive analytics and precision dosing, remote monitoring and developmental screening, child protection and mental health risk prediction, and population-level resource allocation. We performed a narrative review searching PubMed, Google Scholar, and specialist repositories for systematic reviews, scoping reviews, and primary studies published 2019-2026. We included articles explicitly specifying a pediatric population (typically under 18 years). We highlight promising but heterogeneous findings across sepsis prediction, remote physiological monitoring, autism spectrum disorder (ASD) screening, precision dosing, child maltreatment risk modelling, and geospatial resource allocation. In all cases, pediatric-specific studies were underrepresented, often reporting smaller, single-center cohorts. Fewer than 1 in 10 FDA-approved medical devices incorporating AI were explicitly approved for pediatric use (as of 2024). While early ethical frameworks such as ACCEPT-AI and PEARL-AI provide guidance on pediatric AI/ML development, pediatric-specific governance, privacy regulation, and algorithmic auditing lag behind those for adult populations. ML/DL/IoT/DS offer unprecedented opportunities to improve the personalization and timeliness of pediatric care. To realize this potential, multi-centerpediatric-specific datasets, rigorous subgroup and developmental-stage analyses, external validation, and pediatric-specific data-governance guidelines will be essential.

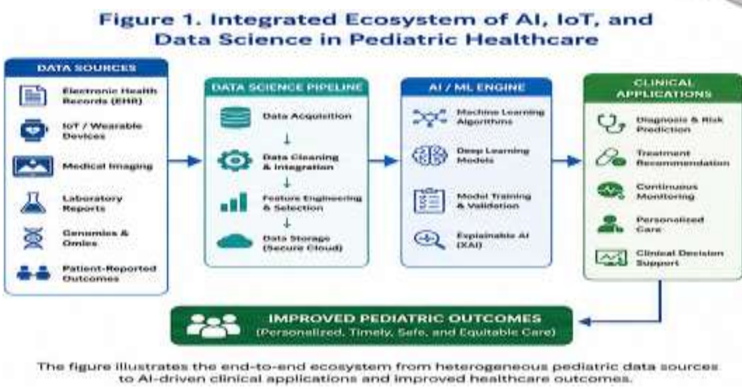
Keywords: artificial intelligence; machine learning; deep learning; Internet of Things; data science; pediatrics; child health; wearable devices; predictive analytics; health equity; algorithmic bias; pediatric data governance.

1. Introduction

Pediatric care presents special challenges compared to adult medicine: physiology and drug metabolism vary with age and developmental stage, clinical presentations differ, and consent/assent procedures must account for a population that cannot legally consent for themselves. These factors limit the use of many clinical algorithms directly trained on mixed-age adult populations. Furthermore, a recent analysis of the US Food and Drug Administration AI/ML database indicates that, out of 692 total devices analyzed through 2024, only 4 (0.6%) were developed specifically for use in children, while only 69 (10.0%) were approved for use in both adults and children (Muralidharan et al., 2023; related work includes an analysis of pediatric health data governance).

At the same time, the intersection of ML, DL, IoT, and DS is generating a growing body of pediatric-specific evidence across four clinical domains: (1) predictive analytics and precision therapeutics, (2) remote and continuous physiological monitoring and developmental screening, (3) child protection and behavioral health risk prediction, and (4) resource allocation at a population level. This review synthesizes the current evidence, with a focus on methodological rigor, and examines how this technical literature interacts with emerging ethical and regulatory frameworks, including ACCEPT-AI and PEARL-AI.

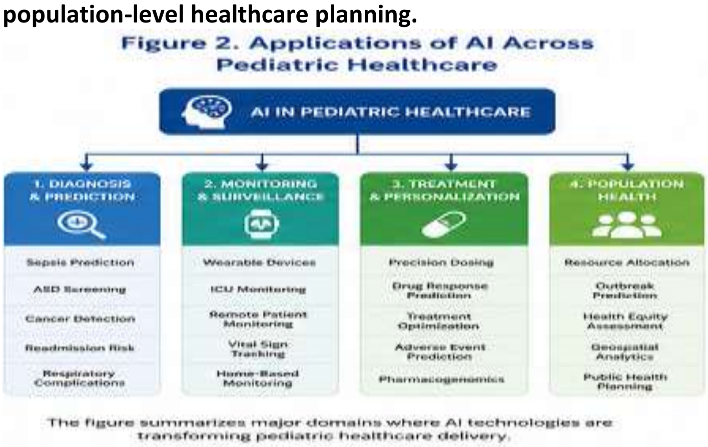
Figure 1 illustrates the overall workflow of AI-driven pediatric healthcare. Clinical data collected from electronic health records, wearable IoT devices, medical imaging, laboratory investigations, and genomic sources are integrated using data science techniques. Machine learning and deep learning algorithms analyze these data to support diagnosis, risk prediction, personalized treatment, and continuous monitoring, ultimately improving clinical decision-making and pediatric outcomes.



2. Methods

This is a narrative, rather than systematic, review; we did not pre-register a protocol. We identified relevant papers using iterative searches of PubMed/MEDLINE, npj Digital Medicine, JAMA, Nature portfolios, preprint servers (medRxiv, arXiv), and other resources using terms related to pediatrics, artificial intelligence, and clinical domains of interest. We limited our focus to (a) systematic/scoping reviews reporting explicit search strategies, (b) large-scale primary studies, and (c) papers published 2019–2026 specifying a pediatric population (<18 years old) of study. We excluded general adult-population papers unless they explicitly discussed pediatric ethical or regulatory frameworks. Furthermore, since this is a narrative, and not a PRISMA-compliant systematic review, we did not score individual studies for methodological bias or prepare a flow diagram. This decision is discussed in detail in Section 9. Finally, we verified all references cited below against their source material to ensure that citations matched actual content, avoiding the pitfalls of other AI-based literature searches.

Figure 2 summarizes the major clinical domains in which AI technologies are currently applied in pediatric healthcare. These include disease diagnosis, continuous monitoring using IoT devices, personalized therapeutic decision-making, and population-level healthcare planning.



3. Predictive Analytics and Precision Therapeutics

3.1 Predicting Clinical Deterioration and Pediatric Sepsis

Pediatric sepsis remains a leading cause of pediatric mortality, and its heterogeneous presentation in children makes diagnosis challenging. A 2024 scoping review identified 27 relevant pediatric sepsis prediction studies, most of which (85%) were single-center and used relatively simple analytic approaches (59% logistic regression), while reporting highly variable discrimination (AUC range, 0.56-0.99) and inconsistent outcome definitions (Tennant et al., 2024). Earlier work using ensemble approaches (random forest and gradient-boosted trees) on intensive-care unit (ICU) physiological and laboratory data demonstrated an ability to predict severe sepsis several days in advance of clinical recognition (Le et al., 2019). The recent publication of consensus Phoenix criteria for pediatric sepsis and septic shock is likely to improve label consistency in future model-development studies (Sanchez-Pinto et al., 2024).

3.2 Precision Dosing and Pharmacokinetic Modeling

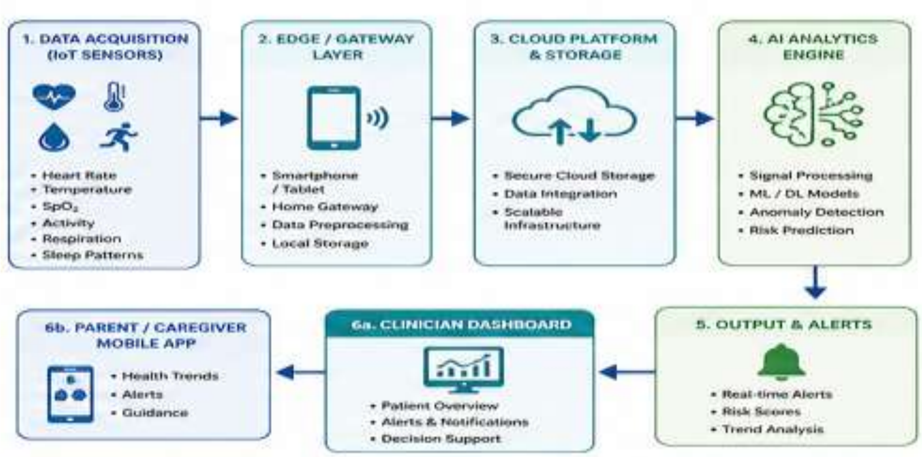
In pediatrics, weight- and body surface area–based dosing is standard, but these approaches do not always account for developmental differences in absorption, distribution, metabolism, and excretion. More recent work is exploring the role of ML methods in precision dosing, either as an alternative or supplement to model-informed approaches such as population pharmacokinetics (PopPK) and physiologically based pharmacokinetics (PBPK). Physiologically based dosing models have been used to estimate appropriate drug doses for specific pediatric populations, addressing the issue of developmental differences in drug metabolism (Zhou et al., 2023). Similar approaches using PopPK/PBPK/ML combinations have been proposed for a range of narrow therapeutic index drugs, including those for which clinical pediatric dosing trials are challenging (Barrett, 2024; Poweleit, Vinks, & Mizuno, 2023).

Table 1 Representative pediatric-specific predictive analytics and precision-dosing studies

Application	Study / Source	Method	Key Finding
Pediatric sepsis prediction (scoping synthesis)	Tennant et al. (2024), npj Digital Medicine	Synthesis of 27 studies (logistic regression, ML/DL)	AUC range 0.56–0.99; 85% single-center; inconsistent outcome definitions
Pediatric severe sepsis / deterioration	Le et al. (2019), Frontiers in Pediatrics	Ensemble ML on ICU physiological/lab data	Demonstrated feasibility of early sepsis risk flagging in critically ill children
Sepsis outcome standardization	Sanchez-Pinto et al. (2024), JAMA	Consensus criteria development (Phoenix)	New standardized pediatric sepsis/septic-shock definitions for future model labeling
Precision drug dosing (general)	Barrett (2024), J PediatrPharmacol Ther	Narrative synthesis of AI-guided dosing	AI/ML as a complement to model-informed precision dosing in children
Physiologically based dosing models	Zhou et al. (2023), CPT: Pharmacometrics & Systems Pharmacology	PBPK modeling review	Computational PBPK tools improve individualized pediatric dose prediction

Figure 3 presents a typical IoT-based pediatric monitoring architecture. Wearable sensors continuously collect physiological signals that are transmitted through a gateway device to cloud-based AI systems. Machine learning algorithms analyze the incoming data and generate alerts that are communicated to clinicians and caregivers for timely intervention.

Figure 3. IoT-Based Smart Pediatric Monitoring Architecture



The figure shows a typical IoT-enabled architecture for continuous pediatric health monitoring and early clinical intervention.

4. IoT-Enabled Remote Monitoring and Developmental Screening

4.1 Wearable Sensors and Continuous Physiological Monitoring

Wearable and adhesive biosensors are playing an increasing role in pediatric hospitals, measuring vital signs and other clinical data continuously and non-invasively. A 2025 review synthesizing 36 published clinical studies of pediatric wearables (2014-2025) suggests that clinical-grade interpretation of these data requires AI but that most studies to date were small feasibility trials without outcome-level validation. Design limitations, including the need for pediatric-specific device development and motion-robust signals, were identified as key translational hurdles (Zheng et al., 2025). A similar scoping review of wireless hospital monitoring during inpatient admission also concluded that most such devices were limited to early validation feasibility studies (Senechal et al., 2023). In one post-surgical use-case example, wrist-worn activity trackers plus ensemble ML algorithms accurately predicted recovery trajectory shifts up to 48 hours in advance of clinical recognition for pediatric appendicitis (Ghomrawi et al., cited in Zheng et al., 2025). Further improvements to this type of algorithm enabled prediction of abnormal recovery three days before diagnosis.

4.2 AI-Assisted Developmental and Neurodevelopmental Screening

There is a large and growing literature on the use of AI methods for autism spectrum disorder (ASD) screening in children, driven in part by the delay between initial concern and definitive diagnosis. A 2025 systematic review examining AI methods for predicting ASD diagnosis in 0- to 18-year-olds identified several studies showing heterogeneity in performance across modalities, including caregiver questionnaires, short home videos, eye-tracking, audio analysis, and neuroimaging (Solek et al., 2025). Similar findings were reported in evidence examining the ability of machine learning algorithms analyzing eye-tracking data to identify ASD in preschoolers, with a focus on addressing potential biases related to gender and race. Overall, these analyses suggest that while most individual studies showed strong discriminative performance, they were limited by convenience samples, insufficient validation, and lack of representativeness of minority populations.

Table 2 Representative IoT and developmental-screening applications in pediatric care

Application	Study / Source	Modality	Key Finding
Hospital/outpatient wearables	Zheng et al. (2025), Bioengineering	36-study review; wrist trackers, adhesive biosensors	AI aids interpretation but most evidence is small, single-center feasibility work
Wireless hospital monitoring	Senechal et al. (2023), Eur J Pediatr	Scoping review of wireless devices	Early-stage clinical validation; reliability testing gaps identified
Postoperative recovery tracking	Ghomrawi et al., cited in Zheng et al. (2025)	Wrist-worn Fitbit + random forest	Detected abnormal recovery up to 48–72 hours before symptom reporting
ASD screening / diagnosis	Solek et al. (2025), Turkish Archives of Pediatrics	Systematic review, ages 0–18	Performance varies widely by modality (video, eye-tracking, EEG, imaging)

5. Data Science for Child Protection and Behavioral Health Risk

5.1 Predicting Child Maltreatment Risk

Electronic health record (EHR)-based predictive models have been developed to identify children at highest risk of maltreatment or its recurrence, using structured and unstructured EHR data plus risk factors (Landau et al., 2025). These studies have provoked especially vocal ethical debates, as false-positives may lead to unwarranted CPS intervention while false-negatives fail to protect vulnerable children. Published analyses of ethical concerns highlight the difficulty of defining “positive” outcomes given the complexity of child maltreatment, the possibility for bias in CPS records, and the need for careful clinical validation prior to deploying such models in practice.

5.2 Predicting Adolescent Suicide and Mental Health Crisis Risk

ML-based EHR models have been developed to estimate short- and long-term suicide risk for children and adolescents. In one large retrospective study using >41000 pediatric patients (ages 10-18) from a single medical center, suicide-risk scores could be estimated at multiple time points during the follow-up period using standard demographic, diagnostic, laboratory, and medication data (Su et al., 2020). More recent systematic reviews of mental health crisis prediction models for adolescents indicate that most have reasonable discriminative performance (AUC approximately 0.68-0.88) but lower positive predictive value and risk of bias due to limited external validation.

6. Data Science for Pediatric Healthcare Resource Allocation

Geospatial analyses and related floating-catchment-area methods have been used to study pediatric healthcare resource allocation, including primary care and specialized consultation. Earlier studies examining access to pediatric primary care highlighted the limitations of distance- and ratio-based approaches while proposing optimization methods to inform physician recruitment and telehealth policy (Nobles, Serban, & Swann, 2014). Similar catchment-area methods have been used to examine pediatric psychiatric consultation access, identifying counties for which new resources or increased telehealth utilization would most decrease disparity, while taking into account socioeconomic, insurance, and stigma-related barriers to care. These data science approaches supplement rather than replace policy-level interventions, such as recruitment incentives for ruralpediatric practice.

Figure 4 illustrates the ethical principles required for deploying AI systems in pediatric healthcare. Key requirements include privacy protection, fairness, transparency, informed consent, explainability, and compliance with pediatric regulatory guidelines to ensure safe and responsible clinical use.

Figure 5 summarizes the current limitations of pediatric AI research and highlights future research priorities. Addressing these challenges will require collaborative multicenter studies, explainable AI techniques, privacy-preserving learning approaches, and robust external validation before widespread clinical implementation.

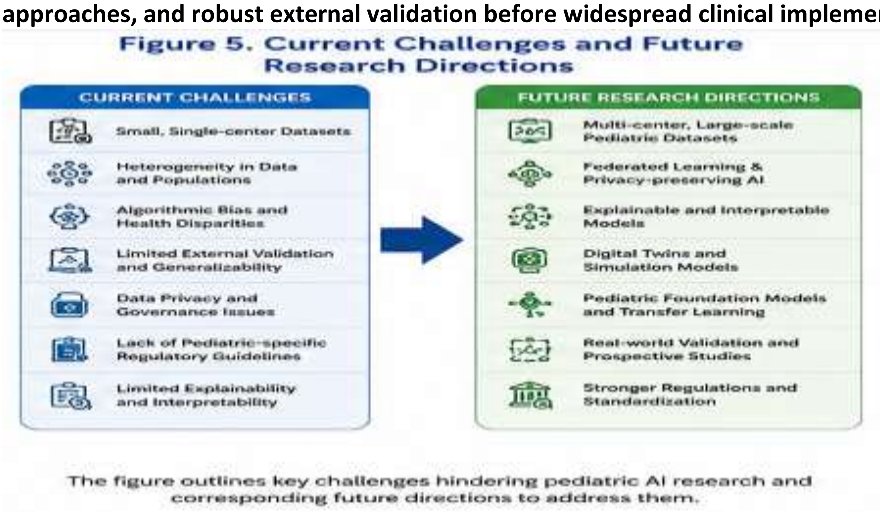
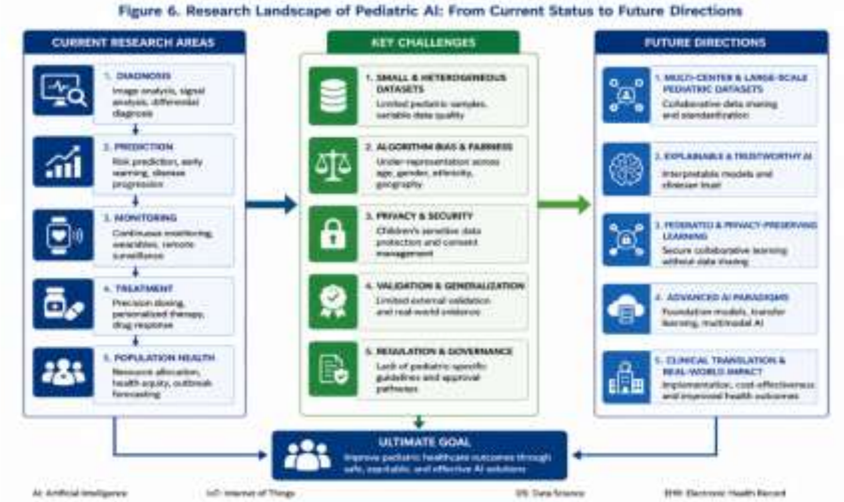


Figure 6 presents the overall research landscape of artificial intelligence (AI) in pediatric healthcare by illustrating the progression from current research areas to future research priorities.

Figure 6. Research Landscape of Pediatric AI: From Current Status to Future Directions



The left panel summarizes the major application domains of pediatric AI, including diagnosis, disease prediction, continuous monitoring, precision treatment, and population health management. The central panel highlights the key challenges limiting the widespread clinical adoption of AI, such as small and heterogeneous datasets, algorithmic bias, privacy and security concerns, limited external validation, and the absence of pediatric-specific regulatory frameworks. The right panel outlines emerging research directions aimed at overcoming these limitations, including the development of large multicenterpediatric datasets, explainable and trustworthy AI, federated privacy-preserving learning, advanced AI paradigms such as foundation models and multimodal learning, and the translation of AI solutions into routine clinical practice. Together, these research directions contribute toward the ultimate goal of delivering safe, equitable, reliable, and clinically effective AI-driven pediatric healthcare.

7. Ethical, Regulatory, and Equity Considerations

7.1 Algorithmic Bias and Health Equity

Children present special challenges in terms of health equity and algorithmic bias: reference populations and disease prevalence vary substantially with age, and few tools explicitly examine developmental age. A 2025 clinical commentary on ML and child health equity discusses how "biases in training data, model construction… and application can lead to or perpetuate inequities but that [these same] technologies can help to elucidate social determinants and promote equity if applied with awareness" (Muralidharan, Burgart, Daneshjou, & Rose, 2025). This perspective highlights several areas of equity-centered work in pediatric ML: predicting non-attendance at scheduled care visits to ensure vulnerable populations receive care, or developing asthma prediction models targeting high-risk populations.

7.2 Pediatric-Specific Ethical Frameworks

As of 2023, two ethical frameworks have been proposed for pediatric AI/ML research. ACCEPT-AI provides pediatric-specific recommendations on age, consent, communication, equity, data privacy, and technology, and was developed as an initial guide due to a lack of available resources at the time of publication despite multiple medical devices already being licensed for pediatric use (Muralidharan, Burgart, Daneshjou, & Rose, 2023). Building on this early work, PEARL-AI (PediatricsEthicAl Recommendations List for AI) is a recently proposed framework to guide the ethical implementation of pediatric AI in practice (Chng et al., 2025). Both works recommend similar pediatric-specific modifications to general ethical guidelines for AI in healthcare, including reporting chronological age alongside developmental age, evaluating performance across developmental subgroups, obtaining child assent when appropriate, and explicitly justifying the use of combined pediatric and adult training sets.

7.3 Data Privacy and Regulatory Landscape

Health data privacy regulations relating to children are rapidly evolving. In the United States, updated COPPA rules took effect in June 2025, with full compliance required by April 2026, explicitly defining the use of children's data for training AI as extending beyond the "normal operations" of a website or service. Similar regulations are expected to be adopted internationally, including in the EU, where the GDPR includes special requirements for processing the data of minors (with ages of legal consent varying between countries). These regulations intersect with children's healthcare data privacy laws (such as HIPAA in the US) and impact healthcare AI development, with pediatric clinical AI developers needing to navigate both consumer-facing digital health/IoT regulations and those specific to children's healthcare data.

7.4 Explainability and Clinical Trust

Since pediatric AI typically incorporates clinical judgment, either by clinicians directly interpreting model findings or by parental/guardian judgment on behalf of the child, model explainability is of particular interest in this population for building trust and facilitating appropriate treatment escalation. Reviews of pediatric wearables and AI applications consistently note limited model interpretability and the absence of pediatric-specific regulatory labels as barriers to clinical adoption (Zheng et al., 2025). Some recent pediatric-focused studies incorporate explainable AI (XAI) methods to highlight features driving model predictions, supporting clinical validation while enabling clinicians to detect spurious correlations.

8. Limitations of This Review

This review has several limitations stemming from its narrative, rather than systematic, nature: (1) we did not formally pre-register this review or apply a systematic search strategy; while we identified studies using systematic/scoping-review methods and applied inclusion/exclusion criteria, this review was not conducted by independent dual reviewers; and (2) we did not formally score individual studies for methodological bias or prepare a PRISMA flow diagram (see Section 9). Furthermore, (3) this review is illustrative rather than exhaustive given the scope of the topic; readers should consult the individual domain-specific reviews cited in this work for a deeper examination of a given area (e.g., pediatric sepsis prediction). And finally, (4) as noted throughout this review, much of the evidence base consists of single-center retrospective studies published in English by researchers in high-income countries, which may limit the relevance to low- and middle-income country settings.

9. Future Directions

Based on this review, we identify four broad areas of opportunity. First, multi-center studies utilizing pediatric-specific datasets stratified by developmental age will be critical to address the underrepresentation of children in many algorithmic training sets and validation cohorts. Second, before introducing pediatric AI/ML tools into clinical practice - and certainly before adopting them for high-consequence applications such as child maltreatment screening - investigators should pursue prospective studies examining model performance across developmental groups and settings. Third, regulatory agencies should create pediatric-specific evaluation guidelines for AI/ML-based medical devices, similar to specialized regulatory pathways for pediatric drug development. At present, fewer than 10% of FDA-approved AI-based medical devices carry a pediatric-specific indication. Finally, collaborations among clinicians, data scientists, bioethicists, policymakers, and others - as outlined in works such as ACCEPT-AI and PEARL-AI - should be viewed as a foundational element rather than an optional add-on to pediatric AI/ML research due to the unique ethical and legal considerations regarding minors' welfare.

Conclusion

The application of machine learning and deep learning in combination with sensor technologies enabled by the IoT and data science is potentially transformative in the context of early diagnosis, treatment personalization, developmental screening, child protection, and access to care. Nevertheless, the pediatric evidence base is less mature than that for adults, with a predominance of single-center studies of small size and limited rigorousness in the literature, while regulatory and data governance frameworks to guide clinical applications are lagging behind innovations and poorly tailored to the needs of children. The focus of research and development should be shifted from the discovery of novel algorithms to be applied in the field of pediatrics to building collaborative multi-center infrastructure, ensuring subgroup analyses in clinical trials, and advocating for the adoption of appropriate regulatory and ethical frameworks such as the ones proposed by ACCEPT-AI and PEARL-AI.

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