Transforming Pediatric Care Through AI: Bridging the Digital Divide in Global Health Informatics

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Abstract

Health informatics and artificial intelligence (AI) technologies present unprecedented opportunities for transforming pediatric healthcare delivery globally. Following post-pandemic digital health acceleration and rising demands for equitable pediatric care, this viewpoint explores how public health informatics systems, combined with AI-powered clinical decision support systems, electronic health record (EHR) integration, and telemedicine platforms, can enhance pediatric care quality and accessibility. Case studies analyzing the Pediatric Emergency Care Applied Research Network (PECARN) clinical decision rules, AI-enhanced neonatal sepsis detection systems, and automated autism screening protocols demonstrate successful health informatics implementations in pediatric settings. Key benefits include improved diagnostic accuracy through computer-aided detection, personalized treatment protocols facilitated by clinical decision support, enhanced accessibility via telehealth platforms, and early intervention capabilities enabled by predictive modeling. However, implementation faces significant challenges, including issues with health information system interoperability, data standardization, gaps in digital health infrastructure, and concerns regarding health equity and access to technology. Strategic recommendations emphasize collaborative development of interoperable health information systems, standardized data governance frameworks, and equitable digital health infrastructure to ensure global pediatric care transformation through public health informatics innovation.

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Transforming Pediatric Care Through AI: Bridging the Digital Divide in Global Health Informatics

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Abstract

Health informatics and artificial intelligence (AI) technologies present unprecedented opportunities for transforming pediatric healthcare delivery globally. Following post-pandemic digital health acceleration and rising demands for equitable pediatric care, this viewpoint explores how public health informatics systems, combined with AI-powered clinical decision support systems, electronic health record (EHR) integration, and telemedicine platforms, can enhance pediatric care quality and accessibility. Case studies analyzing the Pediatric Emergency Care Applied Research Network (PECARN) clinical decision rules, AI-enhanced neonatal sepsis detection systems, and automated autism screening protocols demonstrate successful health informatics implementations in pediatric settings. Key benefits include improved diagnostic accuracy through computer-aided detection, personalized treatment protocols facilitated by clinical decision support, enhanced accessibility via telehealth platforms, and early intervention capabilities enabled by predictive modeling. However, implementation faces significant challenges, including issues with health information system interoperability, data standardization, gaps in digital health infrastructure, and concerns regarding health equity and access to technology. Strategic recommendations emphasize collaborative development of interoperable health information systems, standardized data governance frameworks, and equitable digital health infrastructure to ensure global pediatric care transformation through public health informatics innovation.

Keywords: Health Informatics; Digital Health, Pediatrics; Clinical Decision Support Systems; Electronic Health Records; Telemedicine; Health Information Systems; Medical Informatics; Artificial Intelligence (AI).

Introduction

Every year, approximately 5.2 million children under five die from preventable causes. Many of these deaths occur in settings where AI-driven diagnostic tools could save lives. Public health informatics and artificial intelligence (AI) are increasingly intertwined in efforts to modernize healthcare information systems [1]. Health informatics provides the foundational infrastructure and standardized data models that enable AI algorithms to function effectively in real-world settings. The COVID-19 pandemic has accelerated digital health adoption globally, creating unprecedented momentum for integrating AI technologies into pediatric care systems. Together, these technologies have the potential to transform healthcare into an efficient system that can serve everyone equitably.

In pediatric health, however, progress has lagged. Researchers inappropriately apply adult datasets to pediatric analyses, potentially compromising care quality. Researchers such as Coghlan et al. [2] explore how inserting adult datasets in pediatric research might produce substandard results and ultimately poor outcomes. Health informatics, data standardization, and AI have predictive analytics capability. Instead of using adult datasets, which might be misleading in pediatric practice, structured health information systems can help standardize data collection functionality globally, which would help get sufficient data for AI analytics. This is an opportunity to enhance global pediatrics.

Public health informatics frameworks enable the effective use of AI in pediatric health to address the sensitive nature of medical research involving children. For example, a multicenter validation study by Ramgopal et al. [3] showed that machine-learning algorithms integrated with standardized EHR systems achieved 98.6% sensitivity and 74.9% specificity in identifying serious bacterial infections in febrile infants. This significantly outperforms traditional clinical assessments. According to Ramgopal et al. [3], the random forest model showed superior diagnostic accuracy (Area Under the Receiver Operating Characteristic curve [AUROC]: 0.96) and could have prevented 68.5% of unnecessary lumbar punctures and maintained high sensitivity for infection detection [3]. Such tools exemplify how AI, when embedded within a robust informatics infrastructure, can enhance pediatric diagnostic accuracy and reduce unnecessary interventions.

In low and middle-income countries (LMICs), where healthcare systems face resource constraints and staffing shortages, the integration of AI and informatics presents an opportunity to improve the quality of life and access in global pediatrics. Yet barriers remain. This viewpoint examines how public health informatics, when combined with AI technology such as predictive analysis, natural language processing (NLP), and machine learning (ML), can transform global pediatric care systems. As highlighted above, the technologies are successfully being used in diagnosing genetic conditions among children. Health informatics-enabled application of AI needs to be further enhanced to cover other crucial areas, including treatment recommendations and accessibility of healthcare services. This viewpoint provides a research roadmap for the transformation of global pediatric healthcare by reviewing the applications of health informatics and AI, along with the challenges hindering the integration of health informatics infrastructure with AI technology in pediatrics. Importantly, the viewpoint will provide evidence-based recommendations that would help in successfully implementing health informatics frameworks that leverage AI technology to improve the global pediatric quality of care.

Population-Level Benefits of Informatics and AI in Pediatric Health

Health informatics and AI pose several benefits that would improve global pediatrics. These technologies can improve accuracy, personalization of pediatric care, accessibility, early detection and intervention, and enhance pediatric mental health. One such benefit is efficiency and accuracy. Algorithm-based diagnostic tools exemplify the effectiveness of modern healthcare technology. For instance, Convolutional Neural Networks (CNNs) have been employed for medical imaging in the accurate diagnosis of pneumonia, leukemia, and retinopathy of prematurity [4,5]. Research also points out that existing AI systems have been either equivalent or superior to radiologists in reading radiographs and CT images [6,7]. This shows that AI improves the efficiency and accuracy of clinical decisions. ML algorithms can analyze the information from electronic health records (EHRs). This functionality offers timely evidence for the clinician to identify the rare cases and the evolution of the disease [8]. For example, deep learning has been adopted in pediatric critical care to identify sepsis from physiological data [9].

Another notable benefit is personalization. Health informatics and AI can produce targeted treatments. AI works on patient characteristics and properly treats different pediatric patients without using a definite general scheme of therapy. ML algorithms play the most critical roles in such personalization. In pediatric oncology, AI-based decision-making tools help the clinician choose a chemo regimen based on the tumor's biomarkers and the patient's properties [10]. It reduces side effects and thus improves the results of the treatment process. The personalization extends to enhancing pediatric mental health. For example, the chatbot, Tess, uses AI to offer children with chronic conditions essential information and support for managing their emotional needs [11]. These tools are particularly effective for readdressing the psychosocial requirements of children.

There is also the benefit of accessibility. Access to good-quality pediatric care is a significant problem. Telemedicine platforms supported by health informatics technology are essential in improving accessibility. By incorporating NLP and real-time analyses, these platforms enable patients, especially pediatrics in rural areas, to seek consultations from specialists in urban areas [12]. These systems have been used most in the LMIC because of the limited infrastructure and workforce to deliver quality care [13]. Health information systems and AI are also being utilized in translations since the language barrier has been an issue in global collaborations in pediatric practice.

The benefit of early detection and intervention cannot be overlooked. Accessibility benefits of health informatics and AI in pediatrics also extend to the opportunity for early detection and intervention. For instance, handheld ultrasounds operated by AI have been used to identify congenital heart disease at early stages in remote areas and have increased the detection proportion compared with normal ones [14]. As for chest radiography, AI in diagnosing tuberculosis and pneumonia has enabled earlier diagnosis in resource-limited environments to enhance prognosis [6]. Apart from diagnostics, health informatics and AI expand the availability of preventive care.

Critical Evidence: Real-World AI Applications Transforming Pediatric Care

Health informatics and AI are not mere concepts in pediatric healthcare, as the technologies have been used for real-life impacts. The following case studies demonstrate both the transformative potential and urgent need for systematic implementation of these technologies in pediatric settings: the Pediatric Emergency Care Applied Research Network (PECARN) Rules, AI in neonatal sepsis, and AI diagnosis of autism spectrum disorder (ASD).

PECARN Rules: Revolutionizing Emergency Medicine

The PECARN Rules are one of the first examples of applying AI analytics in pediatric emergency medicine. PECARN is a large-scale coordinated network of hospitals for children's emergency care enhancements. In the present study, PECARN used AI and statistical analysis to determine predictors of high risk of clinically significant traumatic brain injury. These predictors, including the mechanism of injury, signs of skull fracture, and age, were incorporated into a clinical decision support tool that helps physicians decide when to order CT scans [15].

Recent validation of PECARN rules in a comprehensive study of 7,542 children with blunt abdominal trauma and 19,999 children with minor head trauma demonstrated exceptional accuracy owing to the use of AI. The study revealed 100% sensitivity for identifying children under 2 years with clinical traumatic brain injuries and 98.8% sensitivity for children 2 years and older [16]. Implementation of the PECARN rules has significantly decreased the need to perform CT scans. This has consequently reduced CT usage in low-risk patients from 25% in the original study to just 12.6%

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in the validation cohort [16]. This approach is a perfect example of how decision support based on AI can ensure the necessary diagnostic depth while keeping the patient's preferences in mind.

Machine Learning for Neonatal Sepsis

Neonatal sepsis is still one of the primary sources of morbidity and mortality in newborns, especially in the Neonatal Intensive Care Unit (NICU). Sepsis identification is the key to time management, but clinical manifestation commonly appears obscure, thus resulting in delayed management. To solve this challenge, a team of clinical researchers proposed AI as an ML model to predict neonatal sepsis, utilizing physiological data gathered in NICUs. The model was trained on enormous amounts of data on neonatal vitals: heart rate variability, respiration, and oxygen index. The model allowed clinicians to start essential interventions much earlier than when sepsis had worsened to severe stages, as shown by the subtle and early patterns it could detect [17].

This was significantly different from the more conventional scoring system with set cut-offs for a neonate's evaluation and diagnosis of sepsis. The study showed that using AI in predicting bronchopulmonary dysplasia (BPD) in preterm infants achieved 88% sensitivity and 91% specificity [17]. This study was conducted across multiple NICUs. It analyzed 61 preterm infants (gestational age 24-31 weeks) and successfully identified the 26 infants (43%) who developed BPD [17]. When using clinical data alone (birth weight, gestational age, and surfactant treatment), the prediction accuracy showed 74% sensitivity and 82% specificity. These results improved significantly to 88% sensitivity and 91% specificity when combined with AI-analyzed spectral data. These results show that the AI model was superior in sensitivity and specificity. This underscores the ability of AI to determine life-threatening disorders and improve the results for vulnerable children.

AI-Driven Autism Diagnosis

ASD is a developmental disorder that affects a person's ability to interact with others, as well as their behavior. Children with early symptoms need to be identified and referred to early intervention programs that may help the child. However, usual diagnostic tools for ASD involve intense, costly techniques and are unavailable in developing countries. The traditional Autism Diagnostic Observation Schedule-Generic (ADOS) takes between 30 to 60 minutes to deliver. Families may wait as long as 13 months between initial screening and diagnosis. AI has been identified as a significant solution-providing concept to address these challenges.

Wall and colleagues at Harvard Medical School created an AI-based screening protocol, which takes information from behavioral and physiological processes to discover indicators of ASD [18]. Their study analyzed 612 individuals with autism classification and 15 non-spectrum individuals from multiple sources. They included the Autism Genetic Resource Exchange (AGRE) and the Boston Autism Consortium. The research tested 16 different ML algorithms to identify the most effective approach for autism classification. The development resulted in an 8-item classifier derived from the original 29-item ADOS Module. This represented a 72.4% reduction in assessment items. This AI-driven approach achieved an accuracy of 100% sensitivity and 100% specificity in the initial validation. It correctly classified all 612 individuals with autism and all 15 non-spectrum individuals. When validated against independent datasets, the classifier maintained performance with 99.7% accuracy on the Simons Simplex Collection and 100% accuracy on the Boston Autism Consortium dataset [18].

This tool works based on ML models, which are based on factors including facial expressions, language features, and gaze directions. Since the changes in these markers are often minuscule, the

AI system can accurately identify children at early risk of ASD [18]. Thus, scalability remains one of the features that make the proposed approach essential and valuable in large organizations.

Current Applications

Health informatics provides the foundational infrastructure that enables AI to have diverse applications in healthcare practice. Currently, health information systems enable technologies to provide mechanisms for diagnostics, treatment planning, decision support, and patient monitoring. Health informatics data management systems like mGene (a molecular diagnostic platform for pathogen detection) demonstrate how AI has proven efficient [19]. The success of health informatics-enabled AI implementations in these areas informs the potential for leveraging health informatics and AI to improve the quality of life through pediatric care. One current application is in diagnostics. Algorithm-based diagnostic tools exemplify the effectiveness of modern healthcare technology. Standardized health information systems help in organizing crucial diagnosis data, while AI uses the organized data to diagnose children's conditions. EHR integration with ML algorithms represents one aspect of AI that has found usefulness in medical imaging. The technology has been successfully used in analyzing medical imaging and diagnosing possible conditions. Various studies have established that health informatics-supported ML systems demonstrate high success rates in diagnosing pulmonary conditions and musculoskeletal abnormalities using pediatric radiographs [4,6]. In particular, clinical decision support systems utilizing AI technology are efficient in detecting medulloblastoma, which is a frequent brain tumor diagnosed among children. A study by Attallah establishes that the new histopathological model is characterized by better diagnostic features relative to traditional techniques of defining tumor subtypes [20]. All these health informatics-integrated diagnostic and AI-powered tools help to minimize misdiagnosis in pediatric practice.

Another important application is in treatment and personalization. The integration of health information systems with AI in treatment planning has revolutionized child care since it allows for patient-tailored treatment. Clinical data from EHRs, including genetic and clinical patient data and data derived from the patient's environment, can be used as input to ML models to estimate the possibility of a positive treatment outcome. This health informatics approach has been more applicable in using decision support systems for pediatric oncology. Clinical decision support systems powered by AI aid clinicians in determining the best chemotherapy regimen based on the tumor features or the patient's attributes [10]. Health informatics-enabled AI is also very essential in enhancing the results of surgeries. Clinical information systems integrated with AI algorithms allow pediatric surgeons to practice surgery using patient-specific models of the child's anatomy through virtual surgical planning. These tools improve accuracy, decrease intraoperative complications, and optimize postoperative rehabilitation [21]. ML algorithms play the most critical roles in such personalization. In pediatric oncology, AI-based decision-making tools help the clinician choose a chemotherapy regimen based on the tumor's biomarkers and the patient's characteristics [14]. This approach reduces side effects and thus improves the results of treatment processes significantly.

Health information systems integrated with AI technologies have also supported innovative technologies in systematic patient care. As an illustration, mobile health (mHealth) platforms with wearable devices such as Oura and Apple Health have become a part of modern preventive care. Such systems use health informatics data collection protocols and AI technologies to analyze physiological data from EHRs and devices, recorded with wearable devices, to check vitals among children with chronic conditions. These systems deliver clinical alarms to clinicians in real time and support early interventions to lower hospital readmission rates [22]. Research by Williams et al. acknowledges that health informatics-enabled programs that assess patients' vital signs in real-time have helped identify sepsis and other complications [9]. Health informatics and AI also enable behavioral and psychological interventions that follow each patient's unique needs. Examples of chatbots include Tess, which uses AI to offer children with chronic conditions essential information and support for managing their physical and emotional needs [11]. These tools are particularly effective for addressing the psychosocial requirements of children and young people while making them more compliant and enhancing the quality of their lives.

There is also a significant application in accessibility and early detection. Access to good-quality pediatric care is a significant problem. Telemedicine platforms supported by health informatics technology are essential in improving accessibility. By incorporating NLP and real-time analyses, these platforms enable children in rural areas to access pediatric specialists in urban areas. These systems have been used most in LMICs because of the limited infrastructure and workforce to deliver quality care. Health information systems and AI are also being utilized in translations since the language barrier has been an issue in global collaborations in pediatric practice.

Challenges in AI-Enabled Pediatric Systems

Technical challenges include poor data quality, integration limitations, and generalizability issues. Ethical and legal concerns encompass data privacy, regulatory gaps, and algorithmic transparency. Socioeconomic factors create persistent disparities in technology access and resource allocation. On technical challenges, data gathering in pediatrics has many challenges. These include small samples, ethical considerations, and inherent variation of the pediatric population [23]. Training of AI models is based on historical data, which can be inadequate, contradictory, or prejudiced. To illustrate, the samples used for dataset construction usually do not accurately represent the demographics regarding age, ethnicity, and, more importantly, economic status [24]. Getting quality data, particularly from LMICs, is difficult due to structural shortcomings and fragmented health information systems. Filling these gaps calls for strong data-sharing platforms and the enhancement of digital architectures to capture and report data that represents the global picture of the pediatric community [25].

Solutions that can be integrated into existing structures and where new AI tools can be implemented represent substantial technical challenges. The problem is based on the fact that the majority of healthcare institutions utilize legacy EHR technology that does not perform smoothly with current AI technologies [26]. A significant factor that acts as a barrier to the proper integration of AI in clinical processes is the compatibility of data format, coding systems, and storage structures. Algorithmic bias poses a significant problem when using health informatics and AI in pediatric care. Using AI models based on biased sample populations means that such AI will reproduce the existing bias in treatment. To illustrate, an algorithm designed based on data collected in high-income countries will likely work sub-optimally in LMICs because epidemiologic profiles as well as models of healthcare delivery differ between these two contexts [27]. Bias errors can also stem from the researcher's assignment to label the training data or the absence of minority groups in data collection.

Ethical and legal issues encompass data privacy breaches, regulatory inconsistencies, and transparency deficits that undermine trust in AI systems. AI in pediatric healthcare involves working with patient data in health information systems, which includes sensitive personal data. Health information from children can also be breached easily since a child's record is sensitive information that impacts their lifelong record [26]. Health data security should be protected under laws like the General Data Protection Regulation (GDPR) in Europe and the Health Insurance Portability and Accountability Act (HIPAA) in the United States. AI ethical issues are also linked to transparency problems brought about by data interpretability. According to Ciecierski-Holmes et al., 70% of AI tools reviewed in LMIC healthcare settings used 'black-box' algorithms [13]. Such algorithms lacked interpretability of their outputs, thus impacting clinician trust and ethical adoption.

Often, technology changes faster relative to regulatory policies. The regulatory framework in pediatrics is a reflection of this dynamic. It is fragmented and varies across nations. Developed nations are at the forefront of developing solid regulatory frameworks to guide the development and deployment of AI in healthcare and other fields. Some countries, such as Singapore, have already created a Model AI governance framework. Other nations, such as the UK and the United States, have tried regulating AI. However, many LMICs lack robust regulations to guide the development and deployment of AI technologies [26].

Socioeconomic disparities manifest in unequal technology access, inadequate infrastructure, and insufficient funding for AI implementation in pediatric healthcare systems globally. Disparities in health informatics and AI technology are a significant socioeconomic factor in the applications in pediatric practice. According to Ciecierski-Holmes et al., 80% of studied AI implementations were in upper-middle-income countries. There was only 10% in low-income countries and 10% in lower-middle-income countries. These findings demonstrate the uneven distribution of AI healthcare technologies globally. Technology is a resource-intensive and continuous element. The economic resources of a nation determine the disparities in technology access, as evidenced by findings by Ciecierski-Holmes et al. [13]. With health equity in mind, improving global pediatrics requires addressing the disparities in technology.

Health informatics and AI implementation require substantial resources. If the global community is committed to leveraging AI in pediatrics, resource redistribution to areas such as LMICs is necessary. Developed nations such as the United States have historically engaged in large-scale aid programs to provide resources to developing areas, especially in crucial fields such as healthcare. Such initiatives are needed for the global adoption of health informatics and AI in pediatrics. Such programs would successfully address the cost aspect of funding the resource requirements for implementing AI in LMICs.

Solutions for Scalable Pediatric AI Adoption

Enhanced Data Quality and System Integration

One important recommendation is enhancing data quality and availability. This recommendation is significant since only 50% of AI healthcare applications in LMICs documented their training datasets adequately [13]. AI is a data-driven technology. The success and functionality of AI systems are dependent on the quality of data in health information systems used to train models. As discussed previously, there is usually a challenge in research data collection in pediatrics, considering the ethical constraints in research. Successful adoption of AI in pediatrics would largely benefit from collaborative efforts to develop a uniform data source that holds pediatrics practice data from diverse regions. This would create uniform data repositories that provide adequate and quality data for the development of health information systems and AI models in pediatric care.

Health informatics and AI technology are meant to improve the already existing system. The current pediatric healthcare system has developed over time to a point where it has reduced disparities in healthcare, especially in developed nations. Integrating AI with existing systems is the best approach to ensure that the technology does not lead to the loss of the current knowledge, but enhances it for better practice outcomes. For this integration to work, it is recommended that open-source platforms be utilized for compatibility. As an example, the already existing EHRs would be a great addition to AI systems adopted in pediatric health [28]. Open-source platforms would ensure that collaborative efforts in application programming interface (API) programming work seamlessly despite geographical differences.

Privacy, Security, and Equity

A major prerequisite in using health informatics and AI in pediatric care is that the privacy and security of each patient's data are expressly safeguarded. Some legal protections relating to the protection of personal information include the GDPR in Europe and the HIPAA in the US. These regulations and similar policies offer a solid legal basis for protecting personal information [23]. Some measures that can be implemented include choosing encryption methods that help protect the data. The use of role-based access controls also provides a meaningful layer of security by controlling the access of data to particular people. Furthermore, federated learning and anonymization have enabled the training of an AI model using patient data without violating the patient's privacy [26]. Healthcare organizations should also set up independent committees to observe data protection and compliance with ethics rules.

Bridging the digital divide is critical to ensuring equitable access to health informatics and AI-driven pediatric care. Investments in digital infrastructure, such as high-speed Internet and cloud computing capabilities, are essential for extending AI benefits to underserved regions.[20] Governments and international organizations should prioritize these investments. The concept of mHealth systems complemented with health informatics and AI provides a sustainable model for delivering healthcare services with limited resource access. These platforms can support diagnostic and consultation services remotely, so the patient does not have to be physically present at the specific location [12]. Collaboration with the communities to localize these platforms will bolster culture and language-specific benefits in pediatrics practice.

Cost-Effective Implementation Strategies

The high costs associated with health informatics and AI development and implementation remain a significant barrier to adoption. Hiring specialized experts during the initial phase of implementation of health informatics and AI, and the cost of training employees to acquire the new skills required for performing artificially intelligent tasks, is expensive. Public-private partnerships (PPPs) can solve this problem by organizing efficient cooperation and cost-effective health informatics and AI technologies. LMIC governments can contract the private sector for the health informatics and AI infrastructure to implement AI systems. These governments should also look at other ways of tackling this problem. To illustrate, development costs are minimized when adopting open-source health informatics and AI platforms. Open-source platforms simultaneously help promote transparency and collaboration [26]. Considerations for health informatics and AI integration in pediatrics suggest that incorporating cost-effective AI use cases can aid in creating solutions that have the most significant advantages. This is especially relevant where there are exceptionally high burdens of disease, such as neonatal sepsis and malnutrition.

Conclusions

This viewpoint has explored how leveraging health informatics and AI can help improve the quality of global pediatric health. We identified the current applications, benefits, and challenges of using health informatics and AI in pediatric healthcare. These technologies show promise in enhancing diagnostic accuracy, bridging gaps in access, personalizing treatments, and addressing longstanding systemic issues in pediatric care.

However, significant barriers remain, including challenges in data quality, technical implementation, ethical governance, and persistent socioeconomic disparities that disproportionately affect low- and middle-income countries. Addressing these challenges through collaborative, equity-driven efforts is essential to realizing AI's potential in enhancing global pediatric care. The tools exist, the need is urgent, and the time for global action is now.

Future research should explore the applications of AI agents in pediatric healthcare delivery. As AI evolves, intelligent agents may represent the next frontier in clinical decision support, patient engagement, and system efficiency. Research is also needed to inform the development of global policies and governance frameworks that ensure the ethical, equitable, and secure use of health informatics and AI in pediatric settings.

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Contributions

RS and JM conceptualized the research. JM and RA, helped structure and review the viewpoint. AM and GT provided helpful suggestions on the content and formatting of the paper. MK structured, reviewed and formatted the viewpoint.

Conflicts of Interest

None declared.

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Abbreviations
AI - Artificial Intelligence
EHR - Electronic Health Record
LMIC - Low and Middle-Income Countries
ML - Machine Learning
NLP - Natural Language Processing
CNN - Convolutional Neural Networks
NICU - Neonatal Intensive Care Unit

Preprint JMIR Publications

BPD - Bronchopulmonary Dysplasia
ASD - Autism Spectrum Disorder
ADOS - Autism Diagnostic Observation Schedule-Generic
CT - Computed Tomography
PECARN - Pediatric Emergency Care Applied Research Network
AGRE - Autism Genetic Resource Exchange
AUROC - Area Under the Receiver Operating Characteristic curve
API - Application Programming Interface
GDPR - General Data Protection Regulation
HIPAA - Health Insurance Portability and Accountability Act
PPP - Public-Private Partnerships
mHealth - Mobile Health

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