STAFF PERSPECTIVE

Unlocking Neonatal Care: Innovative Technology's Promise in Low-to-Middle Income Countries

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Key Points

There is a critical role of artificial intelligence (AI) and virtual reality (VR) in revolutionising neonatal care and reducing neonatal mortality rates. AI has the potential, through machine learning and data analytics, to assist healthcare professionals in early identification and precise diagnosis of critical conditions, ultimately leading to improved outcomes. Additionally, AI and VR both offer opportunities in remote monitoring, telemedicine, and real-time decision support. This is especially crucial in low and middle income countries (LMICs) as it provides accessibility to healthcare and cost effective solutions. This essay delves into specific case studies, including predictive models for neonatal sepsis, immersive VR for training, and AI-driven analysis of infant cries to diagnose asphyxia. This essay will discuss the benefits of AI and VR in neonatal care, from early detection to resuscitation in LMICs. However, the limitations and challenges of AI implementation, including the need for high-quality data, potential biases, and ethical concerns are also acknowledged. The importance of a balanced approach, combining technology's capabilities with personalized care to advance neonatal health, improve outcomes, and reduce neonatal mortality rates worldwide must be underscored. This is because while AI and VR technologies offer valuable tools for improving healthcare delivery and outcomes, they cannot replace the personalized care provided by healthcare professionals. A balanced approach that integrates AI and VR with personalized care ensures that neonates receive comprehensive and holistic care that addresses their individual needs and circumstances.

Keywords: Neonatal care, artificial intelligence, virtual reality, sepsis, asphyxia

Introduction

Just 2 years ago, mortality rates were at 5 million children's death before reaching their fifth birthday, and an additional 2.1 million deaths in individuals aged between 5 and 24 years. Regrettably, a significant portion of these fatalities could have been averted through primary factors. These factors include fair access to healthcare services, high-quality provision of healthcare services for maternal before, after and during pregnancy and more education of how to enhance neonates' well-being[1-3]. In the fight for equality, reports also indicate that the survival prospects of children remain significantly disparate depending on their place of birth, with the greatest challenges being observed in sub-Saharan Africa and southern Asia[1]. Nevertheless, these primary factors cause nearly 80% of neonatal fatalities varying based on the specific region and stage of neonatal development[2]. In 2007, roughly 75% of neonatal fatalities stem from three main factors: prematurity (28%), sepsis and pneumonia (26%), and asphyxia (23%)[3]. Today, we have arrived at nearly the same damning statistics[4]. Notwithstanding neonatal survival after the precarious fight for life, premature birth and asphyxia can still lead to enduring neurological damage and cognitive deficits among those who survive.

Therefore, this essay will explore how predictive model machine learning and immersive virtual reality (VR) can help septic shocks. It will also look into VR's role in the management of asphyxia, as well as deep machine learning. Lastly, artificial neural networks and their potential to benefit neonates with low birth weights in lower middle income countries (LMICs) will be discussed.

Artificial intelligence (AI) holds immense promise in revolutionising the landscape of neonatal care and reducing the occurrence of neonatal deaths. By harnessing the power of machine learning and data analytics, AI technologies can assist healthcare professionals in early identification of high-risk neonates and precise diagnosis of critical conditions. These algorithms can analyse vast amounts of medical data to provide timely insights that aid in preventing complications and improving outcomes. The evolution of AI, its potential to enhance neonatal care extends to remote monitoring, telemedicine applications, and real-time decision support, which may ultimately contribute to a substantial reduction in neonatal mortality rates. In many LMICs, access to healthcare services, particularly in rural and remote areas, is limited. Families may have to travel long distances to reach healthcare facilities, which can delay medical attention for high-risk neonates. Early identification of high-risk neonates facilitates targeted interventions, even in settings with limited access to healthcare. LMICs may have a higher prevalence of risk factors for neonatal morbidity and mortality, such as preterm birth, low birth weight, birth asphyxia, and neonatal infections[5].Early identification allows for targeted interventions to address these risk factors, potentially reducing adverse outcomes. Early identification of high-risk neonates enables efficient allocation of limited resources, such as neonatal intensive care unit (NICU) beds, ventilators, and medications, to neonates who need them most. Early identification of high-risk neonates not only reduces immediate neonatal mortality but also has long-term implications for health outcomes. Prompt interventions can prevent complications and disabilities, improving the quality of life for survivors and reducing the burden on families and healthcare systems. With greater access to education on neonatal sepsis and its early signs, there would be awareness among healthcare providers, caregivers, and communities about the importance of prompt recognition and treatment. This heightened awareness may lead to earlier identification of neonatal sepsis cases, allowing for timely intervention and potentially reducing the risk of neonatal death.

Sinister Septic Shock

Sepsis in neonates, a critical condition characterized by systemic infection, presents a substantial uphill climb in the realm of neonatal healthcare. As one of the leading causes of morbidity and mortality among new-borns, sepsis poses complex diagnostic and therapeutic hurdles. Contrary to older individuals, neonates display subtle symptoms, and several conditions mimic neonatal sepsis. Blood cultures, which are the gold standard for neonatal sepsis, exhibit reduced sensitivity owing to unique features of the neonatal population. These factors include the volume of blood introduced, the administration of prenatal antibiotics, the degree of bacteraemia, and the capabilities of the laboratory[6]. The vulnerability of neonates to infections, coupled with their underdeveloped immune systems, renders them highly susceptible to sepsis. Understanding the nuances of sepsis in this delicate population is paramount for early detection, timely intervention, and improved outcomes.

In the Monroe Carell Jr. Children's Hospital at Vanderbilt, predictive model machine learning has been developed for the NICU population focussed on late-onset neonatal sepsis[7]. Machine learning is a subset of AI. Its bedrock is erecting novel predictive models from data through an extensive search over wide ranges of models and parameters, then perform subsequent validation[8]. The objective was to develop brand-new continuous risk-assessment tools for neonatal sepsis using electronic medical records of 299 infants, enabling earlier disease detection and better treatment options. Treatment specificity was weighed at the level of the physician, safeguarding the model's sensitivity and specificity levels of detection[6].

There are 2 main benefits of adopting machine learning for the diagnosis of neonatal sepsis. Since further invasive blood tests are not necessary in such a predictive modelling framework, this model is non-invasive. This is particularly important in neonatal care, lowering risk of infections or potential complications. Blood loss from diagnostic sampling is the leading cause of anaemia in low birth weight infant hospitalisation[9]. Therefore, every attempt to reduce additional blood sampling is beneficial to the already struggling neonate. Beyond that, thorough investigations have studied preterm infants and concluded that they have a heightened sensitivity to pain and stressful stimuli[10]. Neonates who undergo persistent hospital procedures may endure physiological changes in pain sensitivity[10]. This process may influence broader stress-arousal systems and could potentially impact the evolving cytoarchitecture of the brain[11,12]. Therefore, these long term effects of neonatal pain and stress should never be overlooked.

Next, the highly-efficient technology offers quick decision-making support which ensures optimal antibiotic administration once sepsis is suspected. The results speak for themselves. The machine learning model was applied to the vast and intricate database of NICU patients, and predictors of late-onset sepsis were identified with ease by comparison with a physician's evaluation[13]. Eight machine learning models were designed to differentiate input data from control and case windows as either "sepsis negative" or "sepsis positive". The algorithms also recognised sepsis-positive new-borns before blood culture data was available, helping to advance treatment. Moreover, when tested with two separate databases, all eight machine learning systems had higher treatment sensitivity levels than the clinicians. Specifically, these models aimed to differentiate patient data collected four hours prior to clinical suspicion of sepsis, indicated by the time of culture draw, from data collected during periods without evidence of sepsis. The eight machine learning models employed were as follows: logistic regression with L2 regularization, naïve Bayes, support vector machine (SVM) with a radial basis function kernel, K-nearest neighbours (KNN), Gaussian process, random forest, AdaBoost, and gradient boosting. Throughout the study, the logistic regression model demonstrated noteworthy performance, nearly matching the highest-performing model across all analyses. With its possible future application in differentiating sepsis negative and positive, more accurate results can be expected with said model. Moreover, it displayed greater resilience to overfitting compared to other models. While the other models showed good performance, they indicated a presence of variance. Therefore, the logistic regression model was elected to be the best learning model[14].

While said pilot study was conducted in a high-income country NICU, it can offer valuable insights and potential applications for LMICs in several ways. Firstly, studies conducted in high-income country NICUs may lead to the development of clinical protocols and guidelines for the management of septic neonatal conditions. These protocols can be adapted to suit the context of LMICs, taking into account differences in available resources, infrastructure, and healthcare practices. Secondly, training modules based on best practices identified in high-income country NICUs can help build the capacity of healthcare workers in LMICs to provide quality neonatal care, even with limited resources. Pilot studies may raise awareness about neonatal health issues and the importance of early intervention among stakeholders in both high-income and low to middle-income countries. Community engagement initiatives can empower local communities to advocate for improved neonatal care services and support policy changes at the grassroots level. Direct application of findings from high-income country NICUs to LMICs may require adaptation and contextualization. Henceforth, pilot studies conducted in these settings can serve as valuable starting points for addressing neonatal health challenges in resource-constrained environments. Collaboration, innovation, and knowledge sharing are key to translating research findings into tangible improvements in neonatal care outcomes across different socioeconomic settings.

Apart from machine learning systems, immersive VR is another platform for constructive growth in neonatal management of sepsis. A three-dimensional technology-driven simulation provides healthcare workers with a real-life situation, that is an ideal training environment15. It is an adaptable learning approach with understudies learning at their own convenience without added staff burden[16]. Substantiated by other studies, immersive VR holds formidable educational potential[6]. Immersive VR technology can be leveraged to improve neonatal care and reduce mortality rates in LMICs by allowing healthcare workers to practice skills in a realistic and safe setting, without risking harm to actual patients. VR-based training programs can be accessed remotely, overcoming geographical barriers and enabling healthcare providers in remote or underserved areas to access high-quality educational resources. This is particularly beneficial in LMICs where access to specialised training facilities or experts may be limited. To supplement education, nursing students participated in a mixed-methods study which assesses the viability of an immersive VR sepsis game. The study cohort comprised 282 third-year pre-registration nursing students from Edinburgh Napier University who were undertaking a care of the acutely unwell module. Nineteen individuals participated in the study, with 74% being female and 26% male. The age of participants ranged from 25 to 45 years[17]. Feedback from participants were optimistic and is witness to the promise it holds. Many students attested that the game was a chance to practice making decisions on their own. The majority also believed taking part in the game boosted their confidence. An opportunity to handle a sepsis case in a real-world setting helped to ease nursing students' anxiety and give them more confidence to enter the clinical settings[18].

Yet, there are some challenges to the introduction of immersive VR to LMICs. As it stands, immersive technologies such as computer-based VR headsets pose significant cost[19]. And LMICs are unlikely to adopt such equipment for widespread training purposes[20]. Yet, there is hope in the second wave of immersive reality technology where mobile devices are poised to host VR application. These are more affordable and offer limited fidelity. While traditional training methods may require expensive equipment, facilities, and travel expenses, such VR-based training programs can be more cost-effective and scalable. Once the initial infrastructure is in place, VR simulations can be easily replicated and distributed to multiple healthcare facilities, reaching a larger number of healthcare providers at a lower cost. Immersive reality boasts essential features like lifelike anatomy that helps foster immersive experiences with intricate detail. Established options like Google Cardboard and other economical devices are also anticipated to dominate the landscape for VR application utilisation[21].

A Baby's Breath and Arduous Asphyxia

Undoubtedly, a baby's first breath after birth is the most difficult one it takes in life. For that reason, asphyxia and respiratory distress syndrome are some of the main causes of neonatal death in the low-income world[22]. Meanwhile, the primary causes of infant demise in 2021 in the United States of America were congenital anomalies, low birth weight, sudden infant death syndrome, traumatic incidents or maternal pregnancy complications[23]. By understanding the root causes of these disparities in neonatal death in LMICs and high income countries (HICs) and implementing targeted interventions, progress can be made towards reducing inequities in neonatal health outcomes and ensuring that all new-borns have the opportunity to survive and thrive, regardless of their geographical location or socioeconomic status.

In Nekemte Referral hospital's NICU in western Ethiopia, a retrospective cohort study recorded 23% of neonatal deaths were caused by asphyxia[24]. In the study, data from 2090 live-born neonates admitted to Nekemte Referral Hospital's neonatal intensive care unit between 2010 and 2014 was gathered retrospectively. Information on predictors, causes, and trends of neonatal mortality was obtained from the neonatal registration book and patient cards using a standardized checklist provided by the World Health Organization (WHO). On the other side of the globe, the same problem persists. A 5-year study conducted in central India showed that 39% and 11% neonatal death, due to prematurity with respiratory distress syndrome and perinatal asphyxia respectively. This study involved 1424 neonates admitted to the NICU within the Department of Paediatrics at LN Medical College and JK Hospital in Bhopal, spanning from January 2013 to December 2017[25].

The electronic Helping Babies Breathe (HBB) curriculum is a robust learning platform to train healthcare workers in neonatal resuscitation. The inaugural version of the HBB curriculum was formulated by the Global Implementation Task Force, established in 2006 by the American Academy of Paediatrics (AAP), comprising various stakeholders. Aligned with the World Health Organization (WHO) Basic Newborn Resuscitation Guidelines and the 2010 Consensus on Science and Treatment Recommendations (CoSTR) by the International Liaison Committee on Resuscitation (ILCOR), the curriculum underwent two rounds of Delphi review to garner consensus among expert reviewers. Subsequently, it underwent field testing in Bangladesh, India, Kenya, Pakistan, and Tanzania before undergoing revisions and eventual release[26]. Nevertheless, it is crucial to schedule manikin-stimulated refresher training to maintain competency of such skills. With limited manpower and resources, LMICs struggle to conduct these refresher trainings. Yet, the ubiquity of cellular networks and smartphones presents an opportunity for productive VR simulations aimed at healthcare workers. There are several reasons why this is advantageous. Unlike an in-person training course, VR simulation through a smartphone tolerates episodic learning at its learner's convenience. Arguably, our familiar medium of videos can also be employed at a refresher course. However, such passive learning modalities when used with an active learning modality like VR promotes participation and memory retention[27,28]. Beyond that, VR training provides a deeper level of individualised learning through game-based automated feedback and incentive-led practice[29]. What may seem simple, like opening baby's mouth, are critical skills that save precious time in foetal ventilation during intrapartum asphyxia. A randomised controlled trial in Nigeria and Kenya surveyed 274 nurses and midwives stationed in labour and delivery, operating rooms, and newborn care units who were enlisted from 20 healthcare institutions. The trial concurred that the VR group showed a greater retention of bag-and-mask ventilation skills at 6 months compared to the control groups[30].

Healthcare can also blend with AI and deep machine learning to combat perinatal asphyxia[31]. Through automated analysis of infant's cry, a machine learning system, called Ubenwa, can identify asphyxia . This is a preliminary study, in which data collection took place in 2018, spanning over a year, at two designated locations in Canada and Nigeria. Data collection took place at the University of Port Harcourt Teaching Hospital (UPTH) in Port Harcourt, Nigeria, and the McGill University Health Centre (MUHC) in Montreal, Canada. The data collected was used to design the software and it was used to hypothesise asphyxia-induced dyspnoea altering the cry wave pattern of affected neonates, since phonation and breathing are controlled by the same primary physiological process. This hypothesis was confirmed in a study where consequential differences in cries of the asphyxiated neonates versus that of the healthy infants were noted. For the study, data was acquired from the Baby Chillanto Database from the National Institute of Astrophysics and Optical Electronics, a research centre sponsored by National Council of Science and Technology of Mexico. The database encompassed cries from 69 infants, including those who are normal, experiencing asphyxia, and deaf. These were further synthesised into 1389 samples[32]. Using deep learning techniques, combining Mel Frequency Cepstral Coefficient (MFCC) with Support Vector Machines (SVM) gives the best results in speech recognition . The link between speech recognition and crying in the context of neonatal asphyxia lies in the potential application of speech recognition technology to analyse the acoustic features of neonatal cries. While traditionally used for recognising human speech, speech recognition algorithms can also process and analyse non-verbal sounds, such as infant cries. MFCCs are widely used in speech recognition because they closely mimic how humans perceive sounds[33]. When MFCCs are input into SVM, the model can accurately predict and classify speech. This is particularly useful when dealing with limited examples and complex data, which is a strength of SVM[34]. Thus, the potent blend of these two computational infrastructures is advantageous in two key aspects. Firstly, the application works with a narrow window of examples. Secondly, being incorporated into a mobile application, the unorthodox deep machine learning model is a convenient diagnostic tool. There are major clinical, societal, and economic advantages to using an neonate's cry as a diagnostic indicator of asphyxia. Opposed to the present procedure requiring a blood gas analyser, this mobile application boasts considerable benefits. As with machine learning neonatal sepsis, this is another non-invasive technique for diagnosis. Pitched towards low to middle-income countries, this tool is as inexpensive as a phone. The application does not require any skill-set to work and results are produced under 20 seconds. Therefore, parents or care-givers may swiftly pick up on asphyxia and reduce delays for life-saving treatment.

However, there are some logistical obstacles and costs that will pose a challenge to the introduction of this mobile application. One of the major obstacles to implementing mobile health applications in LMICs is the irregular funding provided by governments. This forces these countries to depend solely on assistance from development partners, multinational organisations, and non-governmental organisations (NGOs)[35]. Secondly, internet bandwidth is scarce and the expenses associated with internet connectivity remain high, making it unaffordable for the majority of people in LMICs[36].

The Size of a Mother's Palm

Yet, there are still other major causes of neonatal death, like preterm birth and low birth weights[37]. In both cases, artificial neural networks (ANN) have been studied for their ability to predict the correlation between variables. Artificial neural networks are dynamic systems that modify their configuration using internal or external data as they learn. Modern neural networks serve as nonlinear tools for modelling numerical data, commonly applied to represent complex connections between inputs and outputs, or to reveal patterns within datasets.

Limited research utilising artificial neural networks have been conducted regarding preterm birth and its primary influencing factors[38]. At Anam Hospital in Seoul, South Korea, researchers employed an artificial neural network framework to examine preterm birth and its main determinants. Main determinants included body mass index, hypertension, diabetes mellitus and others[39]. These data were collected from 596 obstetric patients. Six distinct machine learning techniques were employed and assessed to forecast preterm birth. Variable importance, which gauges a variable's impact on model efficacy, was utilised to pinpoint significant factors influencing preterm birth. In the study, several variables with potential impacts on birth weight were recognised. Input variables for the ANN model included factors like smoking habits, ethnicity, maternal age, weight prior to the last menstrual cycle, presence of hypertension and several other factors. Then, the artificial neural network architecture utilised data from various birth instances in medical facilities. When tested against regression test and random forests model, the neural network demonstrated high accuracy[40]. The final assessment of the test dataset revealed that the model exhibited the ability to precisely predict birth weight with a perfect accuracy rate of 100%, with the given input variables[41]. Accurate prediction of birth weight can help identify pregnancies at risk of adverse outcomes. This early identification allows healthcare providers to implement targeted interventions and provide appropriate prenatal care to improve maternal and neonatal outcomes. Furthermore, LMICs often face resource constraints in healthcare, including limited access to prenatal care, skilled birth attendants, and medical facilities. Predictive models for birth weight can help optimise resource allocation by identifying high-risk pregnancies that require additional support and interventions, thus maximizing the impact of limited resources on maternal and neonatal health. Accurate prediction of birth weight enables healthcare providers to tailor antenatal care interventions based on individual risk profiles. For instance, pregnant women at risk of delivering low birth weight infants may benefit from closer monitoring, nutritional support, and early initiation of interventions to prevent complications. This approach can be adapted and applied in LMICs to predict low birth weights. While there have yet to studies in LMICS using artificial neural networks to predict neonatal birth weights, the potential for anticipatory enhanced prenatal care is still untapped and is an area for exploration.

Are All that Glitters Gold?

There are clear advantages to introducing AI into neonatal care, however it begs the question: What limitations or challenges do we still face? Primarily, accurate AI tools require high-quality data to be fed into its system. Datasets need to be comprehensively documented to construct the model. Here, there are several pitfalls to be mindful of, like limited sample sizes, inadequate management of missing data, and the evaluation of heterogeneity across distinct population segments. Since AI algorithms utilise prior data to detect patterns and produce outcomes, errors and prejudices present in the input data can be reinforced and amplified by the model. Additionally, the absence of certain factors or demographic groups may lead to subpar performance of the algorithm[42]. Furthermore, careful attention should be warranted to detect any inadvertent biases against marginalised groups that might inadvertently exist within the AI model developed[43]. A further limitation concerns the various ethical and jurisdictional challenges that follow the use of machine learning. For instance, in scenarios where the validated algorithm errs, the question of accountability arises. Our ability to attribute responsibility to the creator or operator is purportedly endangered by machines capable of functioning based on flexible rules and adapting to new behavioural patterns. This alleged widening gap is concerning as it jeopardises both the ethical principles of society and the fundamental concept of liability in legal frameworks. The adoption of AI might result in a lack of identifiable parties accountable for any resulting harm. The full extent of the risk remains uncertain, and reliance on machines will significantly constrain our capacity to assign responsibility and assume control over decision-making processes[44].

Conclusion

The blend of AI into neonatal care offers a transformative approach to addressing the complexities of neonatal health and reducing mortality rates. The potential of AI to analyse vast amounts of data, identify high-risk cases, and provide timely insights holds the promise of revolutionising early diagnosis and intervention. The advancement of AI technologies can enhance healthcare systems and remote monitoring. However, it is paramount to approach the implementation of AI in neonatal care with ethical considerations and keep our human touch, and personalise care that remains integral to the healthcare process. By focussing on AI's capabilities whilst maintaining a balanced approach, we can hope towards a future where neonatal health is augmented by cutting-edge technology, leading to improved outcomes and a significant reduction in neonatal mortality. ◂

Declarations

Deborah Yong Yujie is a staff writer on the editorial board of the TSMJ, and was asked to contribute an invited Staff Feature to the TSMJ Volume 23. The author declares that the article was written in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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