Title
Emerging Opportunities Provided by Technology to Advance Research in Child Health Globally

Authors
van Heerden, Alastair
Leppanen, Jukka
Rotheram-Borus, Mary Jane
et al.

Publication Date
2020

DOI
10.1177/2333794x20917570

Peer reviewed

Global Pediatric Health
Volume 7: 1–9
© The Author(s) 2020
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/2333794X20917570
journals.sagepub.com/home/gph
SAGE

Emerging Opportunities Provided by Technology to Advance Research in Child Health Globally

Alastair van Heerden, PhD[1,2], Jukka Leppanen, PhD[3], Mary Jane Rotheram-Borus, PhD[4], Carol M. Worthman, PhD[5], Brandon A. Kohrt, PhD[6], Sarah Skeen, PhD[7], Sonja Giese, BSc (Hon)[8], Rob Hughes, MB ChB, MPH[9], Lisa Bohmer, MPH[10], and Mark Tomlinson, PhD[7]

Abstract

Current approaches to longitudinal assessment of children's developmental and psychological well-being, as mandated in the United Nations Sustainable Development Goals, are expensive and time consuming. Substantive understanding of global progress toward these goals will require a suite of new robust, cost-effective research tools designed to assess key developmental processes in diverse settings. While first steps have been taken toward this end through efforts such as the National Institutes of Health's Toolbox, experience-near approaches including naturalistic observation have remained too costly and time consuming to scale to the population level. This perspective presents 4 emerging technologies with high potential for advancing the field of child health and development research, namely (1) affective computing, (2) ubiquitous computing, (3) eye tracking, and (4) machine learning. By drawing attention of scientists, policy makers, investors/funders, and the media to the applications and potential risks of these emerging opportunities, we hope to inspire a fresh wave of innovation and new solutions to the global challenges faced by children and their families.

Keywords

maternal, new born and child health, child development, digital health, developmental measurement

Received November 11, 2019. Received revised February 4, 2020. Accepted for publication March 6, 2020.

Introduction

Recognition of the early years as a domain of global importance and the inclusion of specific child development indicators in both the Sustainable Development Goal framework[1] and the United Nations Secretary General's Global Strategy for Women's, Children's and Adolescents' Health[2] have refocused attention on critical "windows of opportunity" for intervention within a life course perspective. The need to ensure that children meet their developmental potential, in the context of rapidly falling child mortality, has inspired the "thrive" agenda within the Global Strategy. However, tracking developmental progress longitudinally is expensive and time consuming, with few existing, valid methods available effectively to measure and monitor at a population level in low-resource settings.[3] Currently, some low- and middle-income countries relay on data collected every 3 to 5 years using Demographic and Health Surveys (DHS) and UNICEF's Multiple Indicator Cluster Surveys (MICS). These tools use a standardized methodology to assess health and well-being, and their outputs can support the

[1]Human Sciences Research Council, Pietermaritzburg, South Africa
[2]University of the Witwatersrand, Johannesburg, South Africa
[3]University of Tampere, Tampere, Finland
[4]University of California, Los Angeles, CA, USA
[5]Emory University, Atlanta, GA, USA
[6]George Washington University, Washington, DC, USA
[7]Stellenbosch University, Stellenbosch, Western Cape, South Africa
[8]Innovation Edge, Cape Town, South Africa
[9]The Children's Investment Fund Foundation, London, UK
[10]Conrad N. Hilton Foundation, Westlake Village, CA, USA

Corresponding Author:
Alastair van Heerden, Human Sciences Research Council, 22 Mbubu Drive, Pietermaritzburg 3201, South Africa.
Email: avanheerden@hsrc.ac.za

monitoring of child health and development. Broadly, the MICS measures developmental potential through the Early Child Development Index (ECDI), which is composed of 4 domains: language/literacy, numeracy, physical, socioemotional, and cognitive development.[4] The ECDI exists as one of many tools with the development of indicators to monitor child development globally remaining an ongoing area of research.[5] Approaches such as these rely on self-report by respondents and observations by trained enumerators. The responses are influenced by social desirability of respondents, training level and professional background of enumerators, and adequate cultural and contextualization of the measures.

First steps toward meeting the need for assessments of children's developmental and psychological well-being include the National Institutes of Health's (NIH) Toolbox,[6] which comprises a validated set of freely available measures that can be used to quickly (2 hours or less) assess cognitive, sensory, motor, and emotional function in a diverse range of contexts.[6] All measures are available electronically for use on an iPad. Rather than requiring highly trained research staff to simultaneously monitor time, record responses, and interact with the child, these electronic assessments simplify test administration and reduce cognitive load, thereby improving data accuracy. Although the NIH Toolbox, and other app versions of psychometric tests, are well described,[6-8] little has been written about how technological innovations might benefit other child assessment methodologies. The challenge is that many of the issues of interest are best examined through methods that require manual collection and coding of unstructured data. Additionally, the cost of this type of research continues to climb outside of low- and middle-income countries, making the need for new approaches a global imperative. Such demands impede scaling up the method for widespread use in research, and are impractical to consider within large-scale service delivery monitoring, evaluation, and learning activities.

The approaches we present emerge directly from our experience in the 2015 Jacobs Foundation conference on "eKIDS: Technologies for Research and Intervention With Children and Youth." This meeting brought together leaders in child development, intervention, and technology in a workshop format to explore how technologies can meet the needs for better Maternal, Newborn, and Child Health (MNCH) research and intervention. We chose a number of innovation and technologies in order to focus with more depth. The review is not a comprehensive list of new technologies but rather a detailed review of a select few promising technologies. The authors declare no competing interest or involvement in the companies, products, and technologies discussed. The approaches we chose based on the meeting are (1) affective computing, (2) ubiquitous computing, (3) eye tracking, and (4) machine learning. Table 1 presents a short summary of each approach and outlines how it fits into our conceptual guide.

Affective Computing

Although not a new concept, recent advances in speech recognition and processing power now make affective computing principles useful in applied or everyday settings. Affective computing is about how machines can be used to understand, interpret, and respond to human emotion.[9] Machine-based recognition of people's emotional state relies on a variety of cues, including voice tone, facial gestures, breathing rate, and galvanic skin responses.

Relevance to Child Health and Development

The trajectory of a child's social-emotional development is strongly influenced by their early environment. Unstimulating environments that are emotionally, socially, and physically unsupportive are known to affect brain development.[17] Linear growth is often used as a proxy for measuring the complex interplay between child and environment due to robust evidence of the long-term consequences of stunting on health.[18] No equivalently simple measure is available to assess early social-emotional development. Acoustic features of a verbal interaction between mother and child such as pitch, speed, vocal rhythm, and turn taking may predict attachment style and can shed light on disrupted affective communication.[19,20] Affective computing technology that could be trained to recognize these patterns might make it possible to gauge social-emotional development from a simple audio sample.

Application

The work of Mehl and colleagues,[21] whose electronically activated recorder (EAR) yields valuable acoustic logs of people's day to day experience, is one example of how affective computing could be put to good use. Laughter, arguments, and silence all can be coded from the EAR data. The Language Environment Analysis (LENA) system is a similar approach targeted at understanding the home environment and childcare of children (LENA Foundation). A small audio recorder is worn by the child throughout the day and environmental audio periodically sampled. These audio data are loaded into the LENA system and are immediately translated into information about the environment of the child. A growing body of evidence exists around the use of LENA as a new methodology to assess language

Table 1. Technologies of Interest, Examples From Relevant Literature, and Research/Assessment Applications.

Research Field	Overview	Example Literature	Example Applications
Affective computing	Affective computing explores how machines can be used to understand, interpret, and respond to human physical and emotion states.	Poria et al[9]	Caregiver facial expressions shape children's behavior and emotions. Studying this phenomena requires time-consuming coding. Automated facial expression coding (AFEC) is a first step to removing this barrier.[10]
Ubiquitous computing	The imagined endpoints of the ubiquitous computing paradigm are inexpensive, low energy, Internet-connected devices that are small and pervasively available in the environment.	Patrick et al[11]	The portable, solar-powered smart under-5 clinic booth uses ultrasound and other sensors to monitor child growth and vitals simply by placing the child in the sensor laden booth.[12]
Eye tracking	Eye tracking technologies estimate direction of gaze by using infrared light reflections from the person's eyes (cornea and pupil). The tracking technologies can be integrated with computer displays.	Jones et al[13]	Eye movement control can be altered in children with ADHD. The ability to direct the eyes inward toward a single point (vergence) in response to an attentional task can be used as an objective marker of ADHD.[14]
Machine vision	Enabling computers to process visual data and derive feature patterns from these images.	LeCun et al[15]	Syndromic genetic conditions often are accompanied by recognizable facial features. DeepGestalt, using machine learning and computer vision, outperformed clinicians in the identification of 200 different syndromes in children.[16]

Abbreviation: ADHD, attention deficit hyperactivity disorder.

development.[22,23] Furthermore, future work could permit automatically classifying affective state as inferred from the recorded vocal expression. Affective computing principles applied to techniques such as the EAR and LENA hold huge potential as natural ethnographic tools. They provide practical, scalable means to gather data that were previously too invasive and tedious to collect, and then code and transform them into information about the child's social affective environment. In addition, the automation of these tools rely on means that their application no longer needs to be restricted to research settings; it is possible to deploy these tools for longer with larger groups, as exemplified in the Providence Talks program in the United States (http://www.providencetalks.org/). A limitation of the approach might be that different cultures express emotion through language in nuanced ways. Without access to recourses, the potential use cases may not be applied systematically to the global population of children (Figure 1).

Ubiquitous Computing

The concept of ubiquitous computing[24] draws on the successive shrinking of room-sized computers to devices so small and easy to use that they disappear from awareness. Personal desktop computers, mobile phones, and wearables (Fitbit, iWatch) illustrate the device ubiquity spectrum. The imagined endpoint is inexpensive, low-energy, miniaturized Internet-connected devices that are pervasively available in the environment to complete everyday tasks. One example is a smart city sensor network that detects areas of high pollution.[25] Together these networked sensors and devices provide the opportunity to monitor and respond to changing environments and contexts in real time.

Relevance to Child Health and Development

Identification of persistent neighborhood conditions that moderate efficacy of early nurturing care interventions offers a pathway to enhance intervention impact and sustainability. Poor infrastructure, elevated violence, overcrowding, and environmental toxicity such as pollution may seriously compromise maternal child functioning and health.[26] Current caregiver-focused models commonly overlook contextual factors. Intensive assessment methods are critical to understand community contexts by tapping conditions and processes in neighborhoods and households.[27] These tools also offer the opportunity for insight into both the patterns and, when combined with affective computing, the emotional quality of caregiver and child interactions. Other advantages of the approach are its ecological validity and scalability, that is, small devices that measure the amount of light

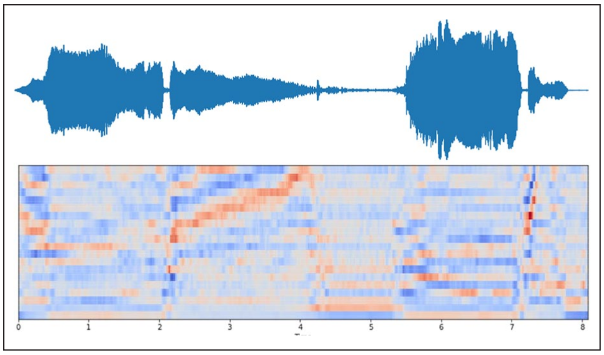

Figure 1. Laughing (top) visualized as a raw wave form and (bottom) representing Mel Frequency Cepstral Coefficients (MFCCs), which are a feature of audio signals that are widely used in automatic speech and speaker recognition.

in crèche could easily be deployed widely and provide evidence of the lighting conditions in the room without worrying that the lights are only being turned on when a monitoring visit takes place.

Application

Ubiquitous computing may offer an affordable community-level solution to the real-time monitoring of the environments in which children are growing, learning, and playing. These data could enable decision makers to locate and monitor environments not supportive of positive life trajectories for children and inform targeted interventions to improve environments in which children live. Using a wireless sensor network, Salathe et al[28] were able effectively to track the proximity of students during a typical day at school and map social networks through close proximity patterns. This enabled the authors successfully to model the spread of influenza-type diseases via individuals who come into close proximity of one another. Similar approaches are being developed to feasibly monitor child-caregiver proximity across the day in rural, low-resource settings (Figure 2).[29-31] The use of ubiquitous computing for child health comes at the increased risk of data being exposed through security breaches of seldom updated embedded devices.[32,33]

Eye Tracking

Remote eye tracking technologies use infrared light reflections to estimate a person's direction of gaze. Low-cost eye-tracking cameras can be integrated with computer displays for unobtrusive data collection on eye movements and visual fixations during everyday screen-viewing situations.

Relevance to Child Health and Development

Problems in neurocognitive development are common in children with birth complications, and in settings with high levels of poverty, undernutrition, parental psychosocial problems, and stress. Efforts to study and manage these problems require accessible measures of developmental outcomes. Traditional tests of visual function (eg, acuity and perimetry), attention, and learning in infants and young children rely on manual assessments of children's visual fixations to pictorial stimuli, and as such, are costly and difficult to standardize.

Application

Fully automated rapid tests have been developed for assessing infant visual function, attention, and sequence learning.[13,34,35] Field tests support the technical feasibility and robustness of eye tracking–based testing of infants in high- and low-resource settings. For example, Forssman et al[35] piloted the use of infrared eye tracking as an alternative to standard cognitive tests in assessing and monitoring early neurocognitive development in children in low-resource settings in rural Malawi. Similar studies have been documented in other low-resource countries.[36-39] In addition to the research assessing cognitive development in groups of children, eye tracking may have utility as a diagnostic tool in the assessment of specific neurodevelopmental problems in individual children. Recent studies have, for example, shown promise in the use of this technology in assessing visual (resolution) acuity,[13] autism spectrum disorders,[40] and attention deficits.[14] If these tests can be incorporated into routine health checkups, they may offer a practical solution for large-scale screening of neurocognitive problems in children.

Machine Vision

One of the most elusive and persistent shortcomings of computers has, until recently, been their inability to process visual data and derive feature patterns from these images. Although even a child can tell you whether or not a photograph contains a dog, image classification has remained a stubborn challenge in computer science. Artificial Neural Networks (ANNs) were originally developed to mimic the human brain. Dendrites receive inputs, and based on these inputs, they produce an output through an axon to another neuron. ANNs were not very effective at these visual recognition tasks. The discovery of Deep Neural Networks, (DNNs), ANNs manipulated to contain multiple layers between the input and output, are, however, very good at this task and have propelled

Figure 2. A child wearing a proximity beacon to estimate time spent with caregiver.

rapid advances in the field over the past 5 years. The rate at which DNNs continue to improve at tasks such as visual recognition are accelerated over this time, although there is concern that these current methods will soon begin to plateau.

A suite of modeling techniques uses multiple processing layers to extract constructs from data by learning increasingly abstract representations of the original data.[41] Deploying the huge amount of visual data now available online, such DNNs are able to process images and accurately predict the content and objects contained in the image.[15] For instance, deep neural nets have been shown to achieve an accuracy of 97.5% when asked to recognize the gender of a person in an image.[42] These advances have, however, been found to have significant bias due to the Western slant inherent in many of the training dataset.[43]

Relevance to Child Health and Development

Positive and frequent caregiver-child interactions are fundamental to healthy child development. Practices of physical care and attending to the infant's basic needs establish a caregiver-child relationship that will influence the social, emotional, and cognitive development of the child. The quality of the caregiver-child bond correlates positively with developmental outcomes of social competence and emotion regulation.[44] The relevance of the field of machine vision to child health and development lies in the opportunity to automatically code, detect, and monitor the world as experienced through the eyes of the child. Applied to tasks such as the automatic analysis of video containing children undertaking tasks of interest and detection of syndromic disorders through facial image analysis, many time-consuming tasks that previously required specialist training could be handed off to machines and routinized.[16,45,46]

Application

Assessment of this relationship currently generally requires specialized, highly skilled practitioners who painstakingly review and code videos of caregiver-child interactions frame by frame.[47] This intensive, unscalable approach would be revolutionized by advances in the field of computer vision. Video footage of such interactions that previously has been coded would need to be located in order to create as large a training dataset as possible. These data then could be leveraged to train a classifier on what different types of interactions look like (using the labels already assigned to the footage by skilled human coders). Once trained, new unlabeled video footage could be fed into the classifier and automatic coding of the interaction performed. This approach offers enormous potential for research in the field of child and adolescent development. Adaptation of systems designed to compete in the Emotion Recognition in the Wild (EmotiW) challenge could be a starting point (https://sites.google.com/view/emotiw2019). The aim of this challenge is to assign 1 of 7 emotions to actors in scenes extracted from popular style movies. The winning entry in 2014 achieved a test set accuracy of 47.67%.[48] MNCH furthermore can be used to characterize material contents and quality of settings in which children live (Figure 3).[49]

Another example of the application of machine vision to child health is through the use of Google StreetView and other visual data sources about the built environment.[50,51] Using these data, it has been demonstrated that income, education, unemployment, health, and crime in London could be predicted with an average classification accuracy of 62% (minimum 47%; maximum 72%).[52]

Risks and Ethical Considerations

The methods and approaches described so far cannot be discussed in a balanced way without reference to both the ethical and contextual challenges rapid changes in technology create. The approaches described here are increasingly straining current ethical frameworks, often resulting in case-based decision-making by Researchers and Ethics Committees partially due to the fact that they

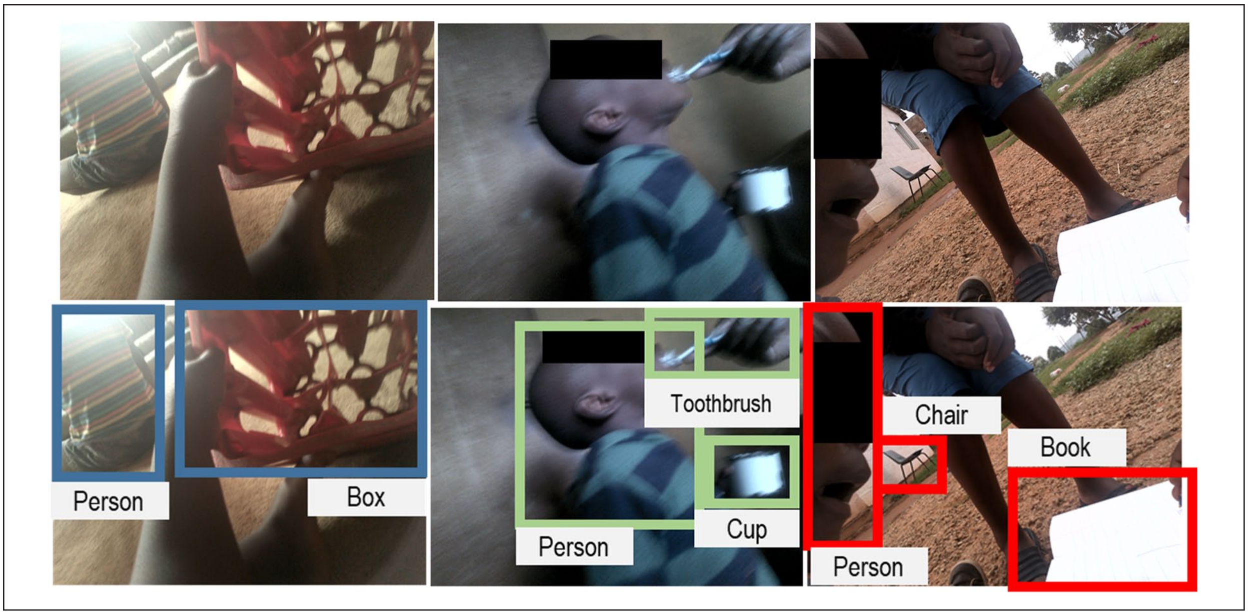

Figure 3. Wearable camera captures from top left (a child at play, dental hygiene and a homework session outside) and what an automated object detection algorithm identified.

run ahead of appropriate legislation.[53] The Emanuel framework for ethical biomedical research states that to be ethical, research must (1) be a collaborative partnership, (2) have social value, (3) be scientifically valid, (4) allow for the fair selection of participants, (5) have a favorable risk-benefit ratio, (6) undergo independent ethical review, (7) require informed consent, and (8) maintain ongoing respect for participants.[54] Classic guidelines such as these are now beginning to be updated to include further protection for participants in the era of biomedical big data analytics, where insights can be generated from social media feeds, personal health monitoring platforms, home sensors, smart phones, and online forums and search queries.[55] One example is the Ethics Framework for Big Data in Health and Research that lays out a set of clear processes for recognizing and resolving issues arising from research with these types of data.[56] Significantly, this framework raises the challenges associated with informed consent as the foundational ethical pillar for these types of data and explores alternative ethically acceptable alternatives such as the principles of respect for persons and social license.

One clear risk to collecting these types of data are privacy concerns that could result from a study data breach. Culturally appropriate approaches to describing these types of data collection and consulting with families are needed to assure understanding and agency for consent and participation.[30,57] Finally, thoughtful solutions are needed to inform how best to act on information revealed from these data. Acute risk of harm, like detection of abuse and maltreatment in a home, require carefully considered risk management protocols.

Ethical Approval and Informed Consent

No ethical approval or informed consent were needed for this study as there was no primary data collection, chart review, or secondary data analysis.

Discussion and Conclusion

Population-based data on child development is essential to improve the lives of children globally and to substantively advance the thrive agenda in the Global Strategy for Women's, Children's and Adolescents' Health[58] as well as to measure progress in meeting Sustainable Development Goals 4.2. Current efforts in this regard include the development of a birth to 3-year population-based measurement framework by the World Health Organization, UNICEF, and UNESCO, the Global Scales of Early Development, and the NIH Toolbox. While such paper-based analogue tools provide much of the functionality required for population-level monitoring and support, these approaches will always be limited by human resources, appropriate in country expertise, time costs, and data quality challenges. These efforts would be strengthened greatly by new technologies such as those discussed in this article, which offer the ability to rapidly analyze and code unstructured data at scale.

While collecting these data maybe be beyond the scope of academic research studies, it is increasingly feasible for many large technology companies. Fields, such as genomics, can show the way with examples of both the potential and challenges of public-private partnerships available.[59] MNCH practitioners, researchers, funders, and policy makers should not ignore this opportunity but rather advocate for collaboration between the owners of these sociobehavioral datasets and the global health community. Managing the potential conflicts of interest between the research objectives, platform user's expectations of data privacy, questions of ownership, wariness toward the commercialization of public sector health data and company objectives of maximizing profits are limitations to this approach.[60]

Rather, global agencies and policy makers such as World Health Organization will need to take a lead through, for example, the eHealth Observatory and related initiatives to ensure ethical, sustainable development of tools that can be scaled up from use in small research studies to routine implementation at the population level. For researchers and implementation partners, the call is to engage meaningfully with these new technologies and grapple with the translation and adaption of these tools, particularly for use in low-resource settings. Opportunity also exists for clearer coordination of efforts that ensure diffusion of local innovation to the global community. The rate of change is a significant risk to this agenda as it will take a concerted effort from all concerned parties to remain abreast of a landscape that is changing at an accelerating pace. To be successful, a balance needs to be found that acknowledges the opportunities, recognizes the risks, and plans for a future that is yet to be invented.

Author Contributions

AvH: Contributed to conception and design; contributed to acquisition, analysis, and interpretation; drafted manuscript; gave final approval; agrees to be accountable for all aspects of work ensuring integrity and accuracy.
JL: Contributed to design; contributed to acquisition, analysis, and interpretation; drafted manuscript; critically revised manuscript; gave final approval; agrees to be accountable for all aspects of work ensuring integrity and accuracy.
MJRB: Contributed to conception; contributed to interpretation; critically revised manuscript; gave final approval; agrees to be accountable for all aspects of work ensuring integrity and accuracy.
CMW: Contributed to conception; contributed to interpretation; critically revised manuscript; gave final approval; agrees to be accountable for all aspects of work ensuring integrity and accuracy.
BAK: Contributed to conception; contributed to interpretation; critically revised manuscript; gave final approval; agrees to be accountable for all aspects of work ensuring integrity and accuracy.
SS: Contributed to design; contributed to interpretation; critically revised manuscript; gave final approval; agrees to be accountable for all aspects of work ensuring integrity and accuracy.
SG: Contributed to conception; contributed to interpretation; critically revised manuscript; gave final approval; agrees to be accountable for all aspects of work ensuring integrity and accuracy.
RH: Contributed to design; contributed to interpretation; critically revised manuscript; gave final approval; agrees to be accountable for all aspects of work ensuring integrity and accuracy.
LB: Contributed to conception; contributed to interpretation; critically revised manuscript; gave final approval; agrees to be accountable for all aspects of work ensuring integrity and accuracy.
MT: Contributed to conception and design; contributed to acquisition, analysis, and interpretation; drafted manuscript; critically revised manuscript; gave final approval; agrees to be accountable for all aspects of work ensuring integrity and accuracy.

Authors' Note

Rob Hughes is now affiliated to the Clean Air Fund, London, UK.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This study was supported by the Jacobs Foundation (Grant ID: CH-8034).

ORCID iD

Alastair van Heerden https://orcid.org/0000-0003-2530-6885

References

1. United Nations General Assembly. *Resolution A.70/L.1. Transforming Our World: The 2030 Agenda for Sustainable Development*. New York, NY: United Nations General Assembly; 2015.
2. Kuruvilla S, Bustreo F, Kuo T, et al. The Global Strategy for Women's, Children's and Adolescents' Health (2016-2030): a roadmap based on evidence and country experience. *Bull World Health Organ*. 2016;94:398-400. doi:10.2471/BLT.16.170431
3. Lake A, Chan M. Putting science into practice for early child development. *Lancet*. 2015;385:1816-1817. doi:10.1016/S0140-6736(14)61680-9
4. Boggs D, Milner KM, Chandna J, et al. Rating early child development outcome measurement tools for routine health programme use. *Arch Dis Child*. 2019;104(suppl 1): S22-S33. doi:10.1136/archdischild-2018-315431

5. Richter L, Black M, Britto P, et al. Early childhood development: an imperative for action and measurement at scale. *BMJ Glob Health*. 2019;4(suppl 4):e001302. doi:10.1136/bmjgh-2018-001302
6. Weintraub S, Dikmen SS, Heaton RK, et al. Cognition assessment using the NIH Toolbox. *Neurology*. 2013;80(11 suppl 3):S54-S64. doi:10.1212/WNL.0b013e3182872ded
7. Peijnenborgh JC, Hurks PP, Aldenkamp AP, et al. A study on the validity of a computer-based game to assess cognitive processes, reward mechanisms, and time perception in children aged 4-8 years. *JMIR Serious Games*. 2016;4:e15. doi:10.2196/games.5997
8. Scott TJL, Short EJ, Singer LT, Russ SW, Minnes S. Psychometric properties of the Dominic interactive assessment: a computerized self-report for children. *Assessment*. 2006;13:16-26. doi:10.1177/1073191105284843
9. Poria S, Cambria E, Bajpai R, Hussain A. A review of affective computing: from unimodal analysis to multimodal fusion. *Inf Fusion*. 2017;37:98-125. doi:10.1016/j.inffus.2017.02.003
10. Haines N, Bell Z, Crowell S, et al. Using automated computer vision and machine learning to code facial expressions of affect and arousal: implications for emotion dysregulation research. *Dev Psychopathol*. 2019;31:871-886. doi:10.1017/S0954579419000312
11. Patrick K, Hekler EB, Estrin D, et al. The pace of technologic change: implications for digital health behavior intervention research. *Am J Prev Med*. 2016;51:816-824. doi:10.1016/j.amepre.2016.05.001
12. Nyasulu T. Smart under-five health care system. In: 2016 IST-Africa Week Conference; May 11-13, 2016; Durban, South Africa. doi:10.1109/ISTAFRICA.2016.7530674
13. Jones PR, Kalwarowsky S, Atkinson J, Braddick OJ, Nardini M. Automated measurement of resolution acuity in infants using remote eye-tracking. *Invest Ophthalmol Vis Sci*. 2014;55:8102-8110. doi:10.1167/iovs.14-15108
14. Casal PV, Esposito FL, Martínez IM, et al. Clinical validation of eye vergence as an objective marker for diagnosis of ADHD in children. *J Atten Disord*. 2019;23:599-614. doi:10.1177/1087054717749931
15. LeCun Y, Bengio Y, Hinton G. Deep learning. *Nature*. 2015;521:436-444. doi:10.1038/nature14539
16. Gurovich Y, Hanani Y, Bar O, et al. Identifying facial phenotypes of genetic disorders using deep learning. *Nat Med*. 2019;25:60-64. doi:10.1038/s41591-018-0279-0
17. Black MM, Walker SP, Fernald LCH, et al; Lancet Early Childhood Development Series Steering Committee. Early childhood development coming of age: science through the life course. *Lancet*. 2017;389:77-90. doi:10.1016/S0140-6736(16)31389-7
18. Dewey KG, Begum K. Long-term consequences of stunting in early life. *Matern Child Nutr*. 2011;7(suppl 3):5-18. doi:10.1111/j.1740-8709.2011.00349.x
19. Kanjo E, Al-Husain L, Chamberlain A. Emotions in context: examining pervasive affective sensing systems, applications, and analyses. *Pers Ubiquitous Comput*. 2015;19:1197-1212. doi:10.1007/s00779-015-0842-3
20. Spinelli M, Fasolo M, Tagini A, et al. Linguistic and prosodic aspects of child-directed speech: the role of maternal child-rearing experiences. *Eur J Dev Psychol*. 2016;13:183-196. doi:10.1080/17405629.2015.1080159
21. Mehl MR, Robbins ML, Deters FG. Naturalistic observation of health-relevant social processes: the electronically activated recorder methodology in psychosomatics. *Psychosom Med*. 2012;74:410-417. doi:10.1097/PSY.0b013e3182545470
22. Wang Y, Hartman M, Aziz NAA, Arora S, Shi L, Tunison E. A systematic review of the use of LENA technology. *Am Ann Deaf*. 2017;162:295-311. doi:10.1353/aad.2017.0028
23. Caskey M, Vohr B. Assessing language and language environment of high-risk infants and children: a new approach. *Acta Paediatr*. 2013;102:451-461. doi:10.1111/apa.12195
24. Weiser M. The computer for the 21st century. *Sci Am*. 1991;265:94-104.
25. Zanella A, Bui N, Castellani A, Vangelista L, Zorzi M. Internet of things for smart cities. *IEEE Internet Things J*. 2014;1:22-32. doi:10.1109/JIOT.2014.2306328
26. Rasanathan K, Damji N, Atsbeha T, et al. Ensuring multisectoral action on the determinants of reproductive, maternal, newborn, child, and adolescent health in the post-2015 era. *BMJ*. 2015;351:h4213. doi:10.1136/bmj.h4213
27. Evans GW. Child development and the physical environment. *Annu Rev Psychol*. 2006;57:423-451. doi:10.1146/annurev.psych.57.102904.190057
28. Salathe M, Kazandjieva M, Lee JW, Levis P, Feldman MW, Jones JH. A high-resolution human contact network for infectious disease transmission. *Proc Natl Acad Sci U S A*. 2010;107:22020-22025. doi:10.1073/pnas.1009094108
29. Heravi BM, Gibson JL, Hailes S, Skuse D. Playground social interaction analysis using bespoke wearable sensors for tracking and motion capture. In: MOCO'18: Proceedings of the 5th International Conference on Movement and Computing; June 2018; Genoa, Italy. doi:10.1145/3212721.3212818
30. Kohrt BA, Rai S, Vilakazi K, Thapa K, Bhardwaj A, van Heerden A. Procedures to select digital sensing technologies for passive data collection with children and their caregivers: qualitative cultural assessment in South Africa and Nepal. *JMIR Pediatr Parent*. 2019;2:e12366. doi:10.2196/12366
31. Poudyal A, van Heerden A, Hagaman A, et al. Wearable digital sensors to identify risks of postpartum depression and personalize psychological treatment for adolescent mothers: protocol for a mixed methods exploratory study in rural Nepal. *JMIR Res Protoc*. 2019;8:e14734. doi:10.2196/14734
32. Chasaki D, Mansour C. Security challenges in the internet of things. *Int J Space-Based Situated Comput*. 2015;5:141. doi:10.1504/IJSSC.2015.070945
33. Patil HK, Seshadri R. Big data security and privacy issues in healthcare. In: 2014 IEEE International Congress on Big Data; June 27 to July 2, 2014; Anchorage, AK. doi:10.1109/BigData.Congress.2014.112
34. Leppänen JM, Forssman L, Kaatiala J, Yrttiaho S, Wass S. Widely applicable MATLAB routines for automated analysis of saccadic reaction times. *Behav Res Methods*. 2015;47:538-548. doi:10.3758/s13428-014-0473-z

35. Forssman L, Ashorn P, Ashorn U, et al. Eye-tracking-based assessment of cognitive function in low-resource settings. *Arch Dis Child*. 2017;102:301-302. doi:10.1136/archdischild-2016-310525
36. Katus L, Hayes NJ, Mason L, et al. Implementing neuroimaging and eye tracking methods to assess neurocognitive development of young infants in low- and middle-income countries. *Gates Open Res*. 2019;3:1113. doi:10.12688/gatesopenres.12951.2
37. Pyykkö J, Forssman L, Maleta K, Ashorn P, Ashorn U, Leppänen JM. Early development of visual attention in infants in rural Malawi. *Dev Sci*. 2019;22:e12761. doi:10.1111/desc.12761
38. Chhaya R, Weiss J, Seffren V, et al. The feasibility of an automated eye-tracking-modified Fagan test of memory for human faces in younger Ugandan HIV-exposed children. *Child Neuropsychol*. 2018;24:686-701. doi:10.1080/09297049.2017.1329412
39. Boivin MJ, Weiss J, Chhaya R, et al. The feasibility of automated eye tracking with the Early Childhood Vigilance Test of attention in younger HIV-exposed Ugandan children. *Neuropsychology*. 2017;31:525-534. doi:10.1037/neu0000382
40. Jones W, Klin A. Attention to eyes is present but in decline in 2-6-month-old infants later diagnosed with autism. *Nature*. 2013;504:427-431. doi:10.1038/nature12715
41. Haddawy P, Wettayakorn P, Wiratsudakul A, et al. Large scale detailed mapping of dengue vector breeding sites using street view images. https://elib.suub.uni-bremen.de/edocs/00107025-1.pdf. Published 2019. Accessed April 2, 2020.
42. van de Wolfshaar J, Karaaba MF, Wiering MA. Deep convolutional neural networks and support vector machines for gender recognition. In: 2015 IEEE Symposium Series on Computational Intelligence; December 7-10, 2015; Cape Town, South Africa. doi:10.1109/SSCI.2015.37
43. Buolamwini J, Gebru T. Gender shades: intersectional accuracy disparities in commercial gender classification. In: Friedler SA, Wilson C, eds. *Proceedings of the 1st Conference on Fairness, Accountability and Transparency*. Vol 81. New York, NY: Proceedings of Machine Learning Research; 2018:77-91. http://proceedings.mlr.press/v81/buolamwini18a.html. Accessed April 2, 2020.
44. Leclère C, Viaux S, Avril M, et al. Why synchrony matters during mother-child interactions: a systematic review. *PLoS One*. 2014;9:e113571. doi:10.1371/journal.pone.0113571
45. James A, Kashyap M, Chua YHV, et al. Inferring the climate in classrooms from audio and video recordings: a machine learning approach. In: 2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE); December 4-7, 2018; Wollongong, Australia. doi:10.1109/TALE.2018.8615327
46. Abirami SP, Kousalya G, Balakrishnan, Karthick R. Varied expression analysis of children with asd using multimodal deep learning technique. In: Sangaiah AK, ed. *Deep Learning and Parallel Computing Environment for Bioengineering Systems*. St. Louis, MO: Academic Press; 2019:225-243. doi:10.1016/B978-0-12-816718-2.00021-X
47. Ochs E, Graesch A, Mittmann A, Bradbury T, Repetti R. Video ethnography and ethnoarchaeological tracking. In: Pitt-Catsouphes M, Kossek E, Sweet S, eds. *The Work and Family Handbook: Multi-Disciplinary Perspectives and Approaches*. London, England: Psychology Press; 2008.
48. Kahou SE, Bouthillier X, Lamblin P, et al. EmoNets: Multimodal deep learning approaches for emotion recognition in video. *J Multimodal User Interfaces*. 2016;10:99-111. doi:10.1007/s12193-015-0195-2
49. Degraen D, Piontak JR, Odgers CL, Schoning J. Neighborhood dashboard: an open tool for child health and neighborhood researchers. In: Society for Research in Child Development (SCRD)–Special Topic Meeting: Technology and Media in Children's Development. Society for Research in Child Development (SCRD-2016); October 27-30, 2016; Irvine, CA.
50. Weichenthal S, Hatzopoulou M, Brauer M. A picture tells a thousand . . . exposures: opportunities and challenges of deep learning image analyses in exposure science and environmental epidemiology. *Environ Int*. 2019;122:3-10. doi:10.1016/j.envint.2018.11.042
51. Nguyen QC, Sajjadi M, McCullough M, et al. Neighbourhood looking glass: 360° automated characterisation of the built environment for neighbourhood effects research. *J Epidemiol Community Health*. 2018;72:260-266. doi:10.1136/jech-2017-209456
52. Suel E, Polak JW, Bennett JE, Ezzati M. Measuring social, environmental and health inequalities using deep learning and street imagery. *Sci Rep*. 2019;9:6229. doi:10.1038/s41598-019-42036-w
53. Kara H. *Research Ethics in the Real World: Euro-Western and Indigenous Perspectives*. Bristol, England: Policy Press; 2018.
54. Emanuel EJ, Wendler D, Killen J, Grady C. What makes clinical research in developing countries ethical? The benchmarks of ethical research. *J Infect Dis*. 2004;189:930-937. doi:10.1086/381709
55. Mittelstadt B. The ethics of biomedical "big data" analytics. *Philos Technol*. 2019;32:17-21. doi:10.1007/s13347-019-00344-z
56. Xafis V, Schaefer GO, Labude MK, et al. An ethics framework for big data in health and research. *Asian Bioeth Rev*. 2019;11:227-254. doi:10.1007/s41649-019-00099-x
57. van Heerden A, Wassenaar D, Essack Z, Vilakazi K, Kohrt BA. In-home passive sensor data collection and its implications for social media research: perspectives of community women in rural South Africa. *J Empir Res Hum Res Ethics*. 2020;15:97-107. doi:10.1177/1556264619881334
58. Fearon RMP, Tomlinson M, Kumsta R, et al. Poverty, early care and stress reactivity in adolescence: findings from a prospective, longitudinal study in a low-middle income country. *Dev Psychopathol*. 2017;29:449-464.
59. Moreno PG, Joly Y, Knoppers BM. Public-private partnerships in cloud-computing services in the context of genomic research. *Front Med (Lausanne)*. 2017;4:3. doi:10.3389/fmed.2017.00003
60. Ballantyne A, Stewart C. Big data and public-private partnerships in healthcare and research. *Asian Bioeth Rev*. 2019;11:315-326. doi:10.1007/s41649-019-00100-7