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Strengthening Health Systems through Responsible AI

An emergent research landscape

Canada

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Executive summary

This discussion paper presents an emergent research landscape that explores linkages between artificial intelligence (AI) solutions and global health. It identifies critical evidence gaps and outlines opportunities to leverage AI solutions responsibly to reduce health inequity and strengthen health systems.

From clinical medicine to public health, AI solutions are advancing how infectious and noncommunicable diseases are handled in terms of diagnostics, preventative care, healthcare planning and delivery, clinical decision-making and care delivery, public health surveillance, drug discovery and development, and responses to health threats. Evidence to guide the practice and use of AI in global health is struggling to keep pace with AI evolution and application. There is no time to waste.

Responsible development and use of AI solutions in a global health context must be predicated on research objectives that address knowledge gaps, consider ethical implications, focus on the needs of underserved populations, target neglected conditions and bring a Global South perspective to the forefront.

The proposed research landscape aims to achieve these objectives by responding to global and health-specific trends, which have a pronounced impact on the research environment. Furthermore, the research landscape offers cross-cutting prerequisites for research, including regulation, policy and governance; data quality and representation; gender equality and inclusion; ethics and sustainability; and Global South-led and equitable partnerships.

This discussion paper presents three proposed entry points for AI and global health research: health services (for example, the health workforce), community (for example, One Health surveillance and solutions), and individual health (for example, self-care). Underpinning the research landscape is the argument that evaluation is a critical requirement at every stage of AI development, deployment and adoption for use, and that scaling AI solutions is a choice that should be carefully considered, intentionally charted and informed by grounded research. When done responsibly, scaling offers extraordinary opportunities to address vulnerabilities and improve lives. Finally, the research landscape aims to ensure impact with evidence and solutions that lead to stronger and more resilient health systems.

Using AI in health settings can lead to outcomes that either reduce or deepen inequities. By advancing the research agenda in a deliberate and strategic manner, the Global South should lead with its expertise and evidence to help shape their own AI solutions that are equitable, safe, rights-based, inclusive and sustainable. Donors and research support organizations also have a key role to play in ensuring AI does not perpetuate inequalities or trample people's autonomy and agency.

This research landscape is a starting point for discussion, exploration and experimentation. With a 2030 deadline to meet the Sustainable Development Goals and advance wellbeing for all, this research landscape offers a roadmap to guide discussions and action among the global research community.

Health is a fundamental human right and a universal concern that impacts everyone. **It is also one of the fastest growing areas of AI application.**

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Introduction

Artificial intelligence (AI) has enormous potential to influence health outcomes and health systems worldwide. As AI solutions are developed and implemented at an increasingly rapid pace around the globe, vast and wide-ranging possibilities are emerging to advance global health objectives. However, advancement will come at a considerable cost if AI solutions are not developed and used responsibly. These costs will be borne disproportionately by individuals and groups experiencing the deepest vulnerabilities, inequalities and other forms of deprivation. This includes women, girls, youth, elderly populations, persons with disabilities, displaced populations and gender-Twelve people.

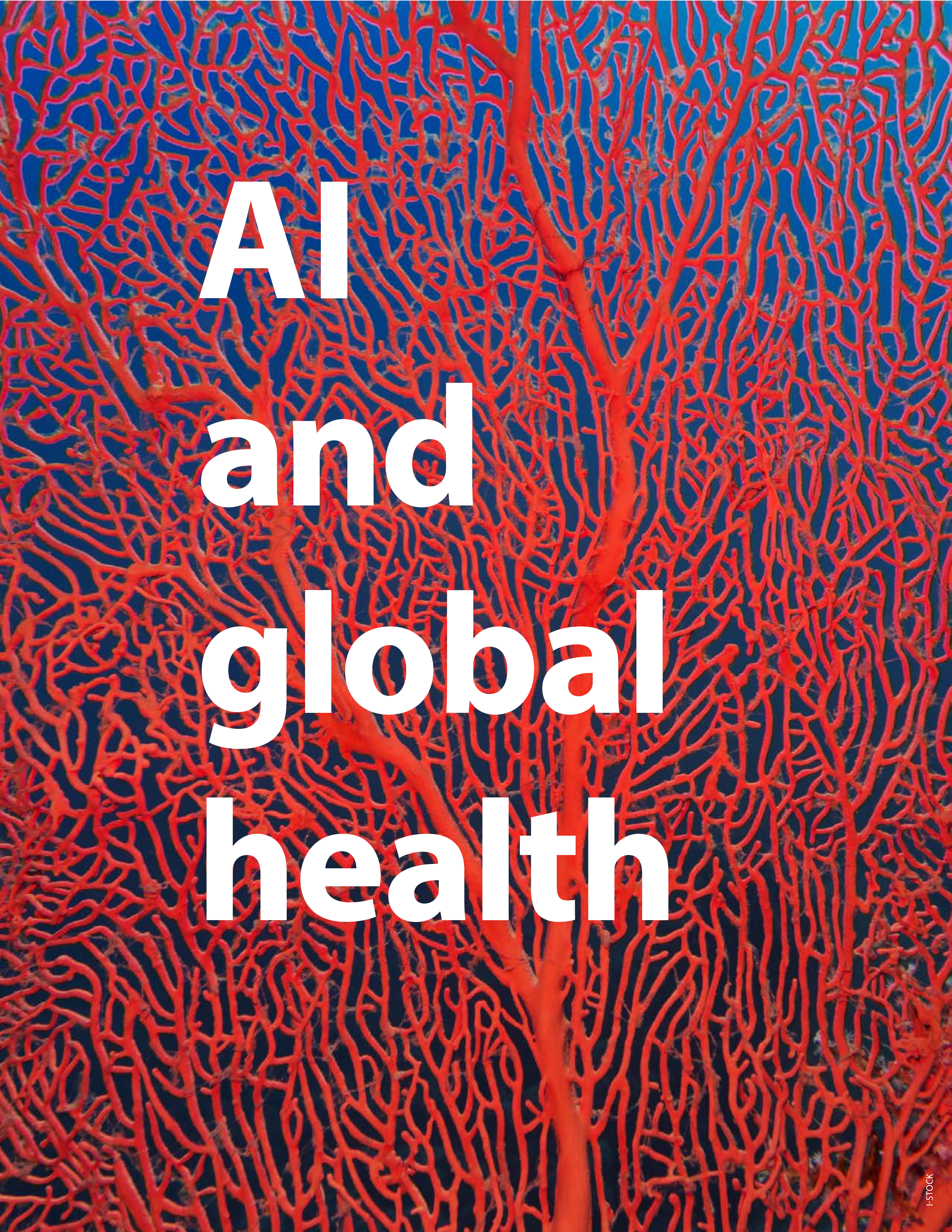
Health represents a fundamental human right that impacts individuals and societies everywhere (UN General Assembly, 1948). The ability to leverage large datasets and digital technology to increase efficiency, reduce costs and expand access to quality care are among the reasons why health is one of the fastest-growing areas of AI application. Across clinical medicine and public health, AI solutions are advancing diagnostics, preventative care, health care planning and delivery, public health surveillance, drug discovery and development, and the management of health threats. Alongside these contributions, the widespread use of AI is leading to heightened risks to patient safety, data privacy and trust in health systems stemming from coded biases, misinformation and disinformation, and a lack of safeguarding regulations, policies and governance structures.

As the world works toward achieving the Sustainable Development Goals (SDGs) while grappling with a polycrisis (Percival et al., 2023), the responsible use of AI can play a supportive role to positively influence the trajectory of health and wellbeing for all. Against an increasingly fast pace of AI adoption, research into AI solutions and their role within a global health context will help establish an evidence base for if, how, for whom, and in what contexts responsible AI solutions can contribute to better health and more prosperous societies. Examining these questions across the Global South requires locally grounded perspectives, insights and leadership to shape how AI-enabled solutions are developed, implemented and governed.

This discussion paper presents an emergent research landscape to leverage responsible AI solutions across the Global South, with a focus on unmet health needs among populations experiencing the highest levels of vulnerability. Drawing on an extensive literature review, analysis of existing AI and global health projects, and a series of key informant interviews, the emergent research landscape is shared as a starting point for conversations and collaboration. It is not intended to be exhaustive or prescriptive in its framing or application.

Several case studies featuring projects funded by Canada's International Development Research Centre (IDRC) and the UK government's Foreign, Commonwealth and Development Office across the Global South are presented to ground and contextualize different concepts and present localized implementation experiences.

AI and global health



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We are witnessing a time with more individual and public health data available than ever before, originating from a vast array of sources — electronic medical records, public health surveillance systems, demographic surveys, health information systems, sensors, wearable devices and more (Sedlakova et al., 2023). Beyond the sheer volume of health data that is available, the multidisciplinary methodologies and technologies used to gather, aggregate and analyze them are evolving at a rapid pace (Chen & Zhang, 2014). Moreover, AI models can blend health data with other health-related data, such as climate patterns, population movements, crop yields, exposure to health threats and other vital data points (Garrett et al., 2022). This capacity to quickly examine and analyze across time, space and sectors allows AI-enabled solutions to generate rich results for complex challenges facing our world today. However, not all AI models are created alike, and as with other technologies, these models reflect the knowledge, attitudes, assumptions, beliefs and biases of the designers, implementers and broader societal forces.

The use of AI spans all six of the World Health Organization's health systems pillars (human resources, service delivery, financing, information systems, governance, and medicines and technologies) (WHO, 2007; Davenport & Kalakota, 2019). Its application ranges from infectious diseases and chronic diseases to the intersection of human, animal and environmental health (One Health) and other underexamined health challenges such as aging and mental health (Zaidan, 2023). The data-rich nature of clinical medicine, public health, One Health, and climate and health lends itself to leveraging AI-enabled solutions. As a result, the quality, credibility and representativeness of data inputted into and used to train AI models fundamentally shape the veracity, credibility and relevance of its outputs. Although this belief is commonly held by AI developers and users alike, a robust and locally relevant evidence-based approach to mitigate the risks, protect the safety, and uphold the rights of individuals and groups toward better health and wellbeing for all, is still lacking.

About AI

AI is a field that has gained significant momentum over the past 15 years in response to the rise of big data, compute power and cloud computing (O'Leary, 2013; Youseff et al., 2008). With roots in multiple disciplines, including computer science, mathematics, philosophy, biology, psychology and neuroscience, the term AI was introduced nearly 70 years ago, in 1956, by American computer scientist John McCarthy.

This discussion paper uses the Organisation for Economic Co-operation and Development's (OECD) definition of an AI system, which is:

> A machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment (OECD, 2023).

The concept of "augmented intelligence" (also referred to as "hybrid intelligence") is used to frame the assistive role of AI to improve decision-making (Zhang et al., 2021). This framing provides an alternative perspective in which humans and machines work together, rather than machines displacing the role of humans from the equation (Pan, 2016).

AI models fall either within the category of discriminative AI, which learns from historical data to forecast or predict outcomes, or generative AI, which is trained on historical data and creates new content. Both types of AI models rely on machine learning (ML), which learns patterns using statistical and mathematical modelling and then applies the patterns to perform or guide tasks and make predictions (Goodfellow et al., 2016).

The rise of generative AI models — propelled by advances in a type of machine learning (ML) called deep learning and the introduction of transformer architecture — has led to the exponential growth and use of large language models (LLMs) (Vaswani et al., 2017). LLMs are trained using vast datasets of text drawn from various online sources to predict the next word in a series of words. A subset (or arguably a superset) of LLMs is large multimodal models (LMMs). Unlike LLMs that can work only on text, LMMs can process text, images, audio and video inputs and can integrate and interpret these multiple modes of data simultaneously.

The need for responsible AI

As a general-purpose technology, AI has far-reaching effects and can have intended and unintended outcomes that can either reduce or deepen inequities. If left unexamined and unaddressed, the design and deployment of different AI solutions will inevitably be shaped by powerful groups and the dominant social and gender norms these groups tend to align with.

The term "responsible AI" describes a set of intentions or normative declarations about how AI solutions ought to be developed, deployed and governed. Responsible AI overlaps with other terms such as trustworthy, ethical, explainable, privacy-preserving and secure AI. IDRC defines responsible AI as "the practice of designing, developing and deploying AI systems that are safe, inclusive, rights-based and sustainable" (IDRC 2024).

To date, the Global North has led the discourse and debate on how best to develop, deploy and regulate AI systems so they are responsible (Foffano et al., 2023). However, a rising tide of insightful and evidence-based conversations from the Global South are promoting locally generated and context-specific models and frameworks for responsible AI (Kong et al., 2023). These models recognize that the current governance architecture and enforcement mechanisms across the Global South are still lagging compared to those from the Global North (Montasterio Astobiza et al., 2022).

Responding to the call for Global South-led evidence on AI governance

Asserting the voice of the Global South, researchers across the multi-regional AI for Pandemic & Epidemic Preparedness & Response Network (AI4PEP) published four papers:

- **Africa:** Decolonizing Global AI Governance: Assessment of the State of Decolonized AI Governance in Sub-Saharan Africa (Ayana et al., 2023) covers 10 countries to examine indicators of decolonial approaches to AI governance. This includes indicators measuring the existence of relevant institutions, examining sovereignty as a priority, and exploring issues of data protection and data use.
- **Asia:** Navigating the Governance of Artificial Intelligence (AI) in Asian Nations: A Focus on India, Indonesia, Malaysia and the Philippines (Nilgiriwala et al., 2024) focuses on national approaches to AI governance and stresses the necessity of regional and international harmonization of AI governance within a concise framework.
- **Middle East and North Africa (MENA):** Exploring AI Governance in the MENA Region: Gaps, Efforts, and Initiatives (Trigui et al., 2024) emphasizes current deficiencies, highlights regional contributions to global AI governance and offers insights into effective frameworks. The study reveals distinctions and trends in the MENA region's national AI strategies, serving as a concise resource for policymakers and industry stakeholders.
- **Latin America and the Caribbean (LAC):** Democratizing Artificial Intelligence for Pandemic Preparedness and Global Governance in Latin American and Caribbean Countries (de Carvalho et al., 2024) explores AI governance through the lens of preventing and responding to the spread of infectious diseases. Specific attention is placed on the critical role of regional and global cooperation, innovation and ethical commitments when responsibly scaling AI applications and democratizing AI knowledge across the region.

Global health and the contribution to AI

Nearly every corner of our planet is experiencing one or more crises that negatively impact individual and public health. This confluence of crises has been labelled by many as a polycrisis (Davies & Hobson, 2022; Tooze, 2022). A polycrisis can be defined as the interaction of multiple crises that intensify suffering, harm and turmoil within societies and overwhelm societies' capacity to respond with effective policies and programs (Percival et al., 2023). Today's polycrisis is characterized by extreme climate events, conflicts, forced displacement, disease outbreaks, economic turmoil and a growing "infodemic," which can seed mistrust in health authorities and undermine public health responses. Women, girls, elderly populations, persons with disabilities, displaced populations and other groups experiencing vulnerabilities suffer disproportionately during events linked to a polycrisis.

For example, the climate crisis is inordinately disrupting the lives of groups experiencing vulnerabilities, leading to displacement, security challenges, and compromised health and wellbeing (Jayawardhan, 2017; Ahmed et al., 2021). This results in precarious living conditions with respect to accessing clean water, clean air, food, waste disposal facilities and health services, including sexual and reproductive health (Calderón-Villarreal et al., 2022; Arunda et al., 2024). These conditions can lead to outbreaks of preventable diseases such as cholera, challenging journeys for girls and women managing menstrual hygiene and reproductive health, and a growing mental health burden across all demographics.

This reality of oppression and compounded disadvantages is heightened across many parts of the Global South. Strengthening equitable, fair and resilient health systems to support groups suffering disproportionately from the polycrisis requires interdisciplinary and intersectoral efforts. Critical to these efforts are high-quality and representative data and information systems that can accurately and coherently track, monitor and respond to human, pathogen and climatic behaviour over time and space.

Opportunities and challenges for AI to advance global health

The potential for responsible AI solutions to meaningfully advance greater health equity and stronger health outcomes is far-reaching. The emergence and evolution of epidemics such as HIV, malaria, tuberculosis, Ebola, mpox and the COVID-19 pandemic have collectively renewed and amplified calls to reimagine or rethink global health solutions and models in ways that respond to current realities and the polycrisis (Burgess, 2023).

Designed and used responsibly, AI algorithms can analyze vast amounts of data — across different sources, sectors and systems. This ability to examine data for health and health-adjacent issues can help address root drivers of poor health, which are often based on social and digital determinants of health.[1]

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[1] The social determinants of health (SDOH) is defined are the social conditions in which people are born, grow, live, work, and age (Marmot, 2005). The digital determinants of health (DDOH) refer to "…the technological factors that are incorporated to provide affordable, accessible, and quality care to consumers enhancing their health-care engagement and experience. Digital determinants refer to factors intrinsic to the technology in question that impact sociodemographic disparities, health inequities, and challenges with care accessibility, affordability, and quality outcomes" (Chidambaram et al., 2024).

A selection of opportunities for applying responsible AI solutions to advance global health objectives includes:

OPPORTUNITY	DESCRIPTION
Analysis and prediction	Looking across vast amounts of structured and unstructured data to identify trends, predict health outcomes, and optimize decision-making for individual and public health (Keshavamurthy et al., 2022).
Health systems optimization	Streamlining logistics; improving patient scheduling, diagnosis and treatment; and optimizing resource allocation across different geographies and needs (Khanna et al., 2022; Schwalbe & Wahl, 2020).
Cost savings	Evaluating gains in productivity and workflow resulting from AI-enabled decision-support, including administrative tasks such as coding and billing (Topol, 2019).
Supporting the health workforce	Relieving health workers from administrative tasks, improving access to evidence-based training and supporting patient outreach (Hazarika, 2020).
Personalized care and precision medicine	Transforming health care provision — from prevention to diagnostics and treatment — by enabling more personalized and tailored care (Raparthi et al., 2020).
Improving patient experiences	Designing AI systems to be empathetic and compassionate when interacting with patients (Morrow et al., 2023).
Drug discovery	Reducing the time and resources required at different stages in the drug discovery process (Blanco-Gonzalez et al., 2023).

Responsible AI solutions can be part of "reimagining global health" toward a less anthropocentric approach and one that values individual needs without compromising community needs, challenges the dualism that separates physical and mental health, and attempts to redress a long history of colonialism (Hindmarch and Hillier, 2023; Burgess, 2023). However, there is also the risk that AI solutions will simply substitute one form of colonialism with another and, as a result, perpetuate or exacerbate disparities based on gender, race, geography, income and other societal factors (Ayana et al., 2023).

Numerous challenges and risks emerge when AI solutions fall short of being responsible. Threats to health and wellbeing resulting from misused and misappropriated AI systems can be categorized as threats to democracy, liberty and privacy; threats to peace and safety; and threats to work and livelihoods (Federspiel et al., 2023).

Responsible use of AI solutions implies upholding human rights (including ethics, equity and inclusion) and considering the legal, policy, regulatory and governance realities of real-world applications.

> *... there is also the risk that AI solutions will simply substitute one form of colonialism with another and, as a result, perpetuate or exacerbate disparities based on gender, race, geography, income and other societal factors.*

A selection of specific challenges or risks for applying responsible AI solutions to advance global health objectives includes:

RISK/CHALLENGE	DESCRIPTION
Weak regulatory, policy and governance	The absence of a robust regulatory, policy and governance environment will enable more harm and reduce incentives for different actors to comply with appropriate standards (WHO, 2024; HealthAI, 2024).
Health data poverty	The failure to address the absence or underrepresentation in datasets renders advances in areas such as precision medicine or other forms of tailored health promotion, prevention or curative services irrelevant, ineffective and potentially harmful (Ibrahim et al., 2021; Cirillo et al., 2020).
Bias and exclusion, perpetuating inequities	Gender and other forms of bias and exclusion can emerge from the selection of health conditions, diversity of developers, representativeness of training data sets and use of results (Drukker et al., 2023; Manasi et al., 2022).
Ethical dilemmas, perpetuating neglect for rights and safety	The failure to protect autonomy; promote human wellbeing, human safety and the public interest; ensure transparency, explainability and intelligibility; foster responsibility and accountability; ensure inclusiveness and equity; or promote AI that is responsive and sustainable (WHO, 2021; Raji et al., 2020).
Corporate overriding, trumping the public good	The restricted access and affordability of certain AI technologies (e.g., LLMs and LMMs) and the dominance of corporate entities in generating many of them could compromise the public good in the interest of corporate profit (WHO, 2024).
Misinformation/ disinformation	The existing guardrails of AI tools used for clinical and public health purposes are insufficient, and the ease with which disinformation and misinformation can be generated is a growing concern (Menz et al., 2024).
Environmental impact	With the backdrop of global warming, a failure to examine the consumption of energy and water, and production of greenhouse gases of AI solutions would be a regretful oversight (Luers et al., 2024; Faiz et al., 2023) [2]

[2] A study estimated that global AI-related energy consumption would be 10 times greater in 2027 that it is in 2023 (de Vries, 2023). Other estimates show that training the 175-billion parameter GPT-3 generated 552 tons of carbon dioxide equivalent (comparable to 123 gasoline-powered passenger cars driven for one year) (Patterson et al., 2021).

CASE STUDY 1

Unlocking AI's potential in Brazil: Democratizing tools to combat disinformation

EDUARDO MARTINO/PANOS

Context: Advances in technology have made access to information more convenient than ever. However, this convenience brings a serious challenge: the spread of fake news. Disinformation, especially when amplified by AI, has become a growing concern due to its potential to sow doubt, sway public discourse and drive mass-scale propaganda (Ryan-Mosely, 2023). The increased accessibility of generative AI has facilitated the proliferation of disinformation campaigns at the national and sub-national levels (Raman et al., 2024). To address these challenges, AI4PEP's AutoAI-Pandemics hub in Brazil developed "Dominique," an AI-powered conversational assistant designed to:

- analyze and evaluate the likelihood of a statement's truthfulness using ML techniques
- promote and popularize fact-checking practices
- provide an accessible tool to help reduce public vulnerability to the impacts of disinformation

Implementation research question: A multidisciplinary team at the Universidade de São Paulo is exploring the question: How can an AI-powered conversational assistant effectively accelerate the information verification process for the public, helping to overcome the challenges of identifying disinformation?

Research in action: Dominique was inspired by the well-known Portuguese-based corpus named Fake.Br (Santos et al. 2018). The corpus includes 7,200 news articles, split equally with 3,600 true news stories and 3,600 fake news stories. The model was trained using gradient boosting (XGBoost), gated recurrent units (GRU) and long short-term memory (LSTM). After analysis, the GRU algorithm performed best in all tests, with an accuracy of 95.7%. Some refinements and enhancements are still needed to ensure the tool can reliably classify fake news in real-world scenarios. The goal is to reach a level of confidence in its performance that guarantees its positive contribution to society.

Results and next steps: As of 2024, Dominique operates in both Portuguese and English. The team continues to improve the performance of models and classifications. The project won the Falling Walls Lab Brazil 2023 and competed in the world final in Berlin, Germany, among the top 100 ideas worldwide. The project was selected for the 2024 edition of Prototypes for Humanity among 2,700 entries from over 100 countries, standing out as one of the top 100 ideas globally.

AI approach: Discriminative AI
AI model: Gated recurrent unit (GRU)
Model maturity: December 2023 (software developed); July 2024 (model testing)

Responsible AI: The solution prioritizes transparency, fairness and ethical considerations in combating misinformation. By emphasizing user-friendly design and educational value, Dominique encourages responsible information consumption and promotes a culture of critical thinking and fact-checking.

Use cases for AI in global health

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Discussion to this point about responsible AI solutions and their applications to global health challenges have been largely theoretical in this paper. Building on this foundation and the high-level overview of opportunities and challenges, the next section introduces two illustrative use cases for responsible AI to advance global health objectives.

- Sexual and reproductive health and rights
- Climate change, health and infectious diseases

The selection of these two interrelated entry points was influenced by IDRC programming priorities for its 2020–2030 Strategy, as well as their importance in meeting the health-related SDGs (IDRC, 2021).

Use case 1: Sexual and reproductive health and rights

Strengthening sexual and reproductive health and rights (SRHR), together with access to services and care, is essential for women, girls, families and societies. Across the life course, when people can access quality SRH information and services and have decision-making power to exercise their rights, they can effectively contribute to their personal wellbeing and that of their families and communities.

According to the WHO, SRH includes:

- SRH cancers
- sexually transmitted infections
- infertility
- intimate partner violence and sexual violence
- maternal and perinatal health
- contraception and family planning
- safe abortion
- menopause
- comprehensive sexuality education
- female genital mutilation

AI technologies and solutions in the SRHR sphere are evolving quickly, yet they are poorly regulated (WHO and HRP, 2024). These solutions use and share sensitive aggregate and disaggregate health data, which is accessed by both public and private actors, opening serious concerns about privacy, intent and ethics (Khosla et al., 2023). Women and girls are not homogenous groups with consistent needs and experiences. The populations most impacted by poor access to SRH information and services are regularly stigmatized, politicized and marginalized.

It is important to consider the benefits and risks AI solutions can introduce to the prevention, diagnosis, medical support and treatment of women and girls (WHO and HRP, 2024). A literature review reveals key benefits such as improving people-centred care, strengthening the quality of care and bridging widening gaps in workforce availability and skills. The same review surfaces risks, including challenging bodily autonomy, breaches in privacy and disinformation in a field fraught with ideologically driven and highly patriarchal narratives (Khosla et al, 2023). For example, a woman may be faced with a decision to seek life-saving treatment or protect herself from being targeted for accessing services such as abortion or post-abortion care that could render her even more vulnerable to social and/or legal repercussions.

Responsibly designed AI-enabled solutions could be leveraged to target the SRHR needs of groups experiencing the highest levels of deprivation and vulnerabilities. This includes adolescents (especially between 10 and 14 years), displaced populations, persons with disabilities, ethnic minorities, gender-diverse individuals, Indigenous groups, sex workers, and other marginalized and underserved groups. A person-centred approach to SRHR recognizes that these different identities and experiences can co-exist and intersect within individuals and groups.

> *The opportunities for responsible AI in sexual and reproductive health and rights are tremendous, but so are the risks and the limited power and voice of those who will bear the brunt of the fallout resulting from the risks.*

Examples of AI solutions in an SRHR context include chatbots to promote sexual health and contraception, advanced machine learning for screening and diagnosing reproductive cancers, and large language models to understand health trends and conduct clinical research and drug discovery work (WHO and HRP, 2024). Although there are many AI innovations to support different elements of SRHR, a focus on equity, accessibility and safety has not always been prioritized (Obermeyer et al., 2019). There is also a growing body of evidence linking SRHR, gender equality and inclusion, and climate change (Bharadwaj et al., 2024). Rising global temperatures and extreme weather events are disproportionately impacting the health and rights of women, girls and other groups experiencing vulnerabilities (Hashim & Hashim, 2016; Islam & Winkel, 2017).

The case studies below, numbered 2 through 6, feature IDRC funded projects, in collaboration with donors such as the UK government's Foreign, Commonwealth and Development Office. Examples are drawn from four regional hubs and targeted funding to Jacaranda Health in Kenya:

- Latin America and the Caribbean (LAC): Center for Artificial Intelligence and Health for LAC (CLIAS)
- Asia: AI for Sexual Reproductive and Maternal Health in South Asia (AI-SAROSH)
- Sub-Saharan Africa: Hub for AI in Maternal, Sexual and Reproductive Health (HASH)
- Middle East and North Africa (MENA): Global Health and AI Network in the MENA region (GHAIN MENA)

CASE STUDY 2

Strengthening prenatal ultrasound services for Indigenous women in Guatemala


GABRIELA PIRIL / IMAGEN CORPORATIVA UNIVERSIDAD GALILEO

Context: Approximately 44% of the population in Guatemala self-identifies as Indigenous, according to the 2018 census. Indigenous populations, Afro-descendants, LGBTQ+ groups and individuals living in poverty face substantial barriers to accessing specialized health care, particularly during the prenatal period when regular monitoring through ultrasound is critical. Recent reports indicate that Indigenous populations, specifically Maya women, have a 1.6 to 2.1 times higher risk of maternal mortality compared to non-Indigenous women (UNFPA, n.d.).

Implementation research question: A multidisciplinary team at the Universidad Galileo is seeking to answer the question of how AI-enabled solutions can assist community-based healthcare providers to perform ultrasounds without the presence of specialized personnel, while being able to interact with Indigenous women in their local language and respecting local context.

Research in action: The NatalIA project team developed an innovative AI-enabled solution that extracts fetal planes from video sequences of fetal ultrasounds. It uses software to extract essential diagnostic features for obstetric evaluations. Currently in the research phase, the project aims to assess the feasibility and capabilities of midwives conducting blind-sweep ultrasound tests with a simulator and the AI tool. This approach will allow for testing a model based on fetal images from real patients for its future implementation in more than 20 Indigenous communities across the country. →

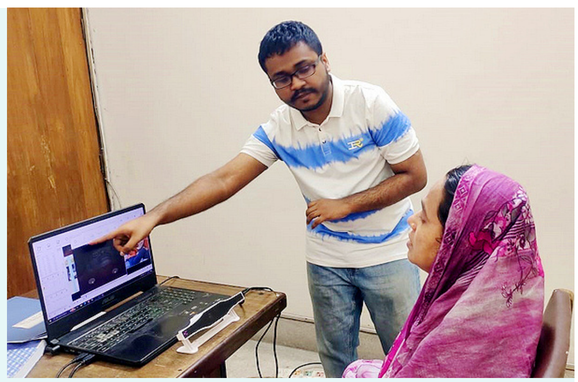
Results and next steps: The project is training midwives and nurses to use the ultrasound capture protocol; it is also validating the AI model. Representing a significant shift in how ultrasound services are provided, the project is decentralizing the process and enabling local healthcare providers to perform ultrasound scans with the support of AI. The next phase will focus on evaluating the technology's adoption by professional midwives from the Universidad Galileo.

AI approach: Discriminative AI
AI model: Convolutional neural networks (CNN)
Model maturity: September 2024 (model testing)

Responsible AI: Ensures transparency and understandability of results, allows for human oversight in decision-making, minimizes potential biases by involving expert evaluations, and protects privacy by excluding real-person data during its validation phase. The datasets used are representative of the target population; they incorporate diverse public data sources and simulate real-world imaging conditions encountered in underserved regions.

CASE STUDY 3

Using AI to detect prenatal and perinatal depression in Bangladesh



DR. MALIHA KHAN MOJLISH

Context: Bangladesh, a country with over 3 million births annually (UNFPA, n.d.), has seen measurable improvements in reducing maternal mortality and morbidity. The issue of mental health care among women during their journey as expectant and new mothers remains a personal and often silent struggle (Insan et al., 2022). Mental health challenges, including depression, anxiety and posttraumatic stress disorder, are associated with adverse outcomes such as preterm birth, low birth weight, and neurodevelopmental impairment in infancy and childhood (Jahan et al., 2021). Many health centres lack psychiatric professionals.

Implementation research question: A multidisciplinary team at Eminence Associates for Social Development in Bangladesh is exploring the question: How can screening tools integrate advanced techniques like facial expression analysis, visual saliency and acoustic features to assist healthcare providers in detecting perinatal depression?

Research in action: The team developed an AI-enabled tool to support non-specialized doctors and nurses to identify and address prenatal and perinatal depression. The tool is being used with pregnant and postpartum mothers from different social strata in Dhaka, employing a two-step approach to train the AI model. First, the solution uses machine learning to recognize general depression patterns. Next, the tool identifies specific features of maternal depression. Using a web-based system, the solution analyzes visual saliency, facial expressions and acoustic features to detect emotions and convey stories that words cannot. While these tools can help improve early detection, they cannot replace the profound human understanding and empathy crucial in mental health care. →

Results and next steps: To date, the system has been used for hundreds of pregnant and postpartum women. AI diagnoses of depression were compared with the PHQ-9 instrument for measuring depression and psychiatrist evaluations. The tools reflect the effort to understand the complexities of the human mind and emotions. The project seeks to move beyond detection toward providing a treatment plan to depressed mothers. Ultimately, it aims to bridge the gap between medical science and human empathy through innovative and non-invasive diagnostic methods.

AI approach: Discriminative AI
AI model: Graph neural network (model trained from scratch)
Model maturity: June 2024 (model testing)

Responsible AI: The project incorporates responsible AI practices in the data collection phase through to design and deployment. The collected dataset reflects the target population's diverse demographics as a means to enhance fairness and mitigate bias. During the model development and validation phases, a "human-in-the-loop" approach is used, with psychiatrists providing clinical validation. The PHQ-9 assessment tool, translated into the Bengali language, will be used to ensure the linguistic relevance of the dataset used to train the AI model.

CASE STUDY 4

Using AI to promote sexual and reproductive health outcomes for adolescents with disabilities in Ghana

I-STOCK

Context: Around the world, an estimated 1 billion people live with some form of disability (WHO, 2011). Although persons living with disabilities have similar SRH needs as others, they face many barriers when accessing relevant information and services for healthy sexuality and safe relationships.

Implementation research question: A multidisciplinary team at the University of Ghana is exploring the question: How can AI be used to promote improved sexual and reproductive health outcomes for adolescents with hearing, speech and visual disabilities in Ghana?

Research in action: Surveys to understand SRH needs were conducted among 400 in-school adolescents living with visual or hearing disabilities. Based on the results, the HASH research team used machine learning to break the barriers inhibiting adolescents living with hearing, speech and visual disabilities from accessing SRH information and services. They developed and piloted a model using Open AI's customized version of ChatGPT (GPTs) based on a small dataset from the field. When some biases were detected, the team generated a larger dataset leveraging pre-trained models from Google's Gemini and OpenAI's ChatGPT. This included developing question–answer pairs to generate data that is relevant, safe, age-appropriate, informative and culturally sensitive.

Results and next steps: Officials from the Ghana Health Service and the Ghana Education Service, as well as several parents, observed the pilot study sessions. The results indicated the need to include sign language features in future iterations. The model is now being tested using TeenChat and #BOT mobile applications with a larger group of adolescents. →

AI approach: Generative AI
AI model: LLM (fine-tuned Gemini and ChatGPT)
Model maturity: July 2024 (testing and deployment)

Responsible AI: The solution is responsibly designed because it engages stakeholders to validate content for adolescents with disabilities. It addresses ethical concerns like bias and cultural sensitivity through prompt engineering. It also promotes inclusivity with accessible online and offline options for users living with visual and hearing loss, ensuring equitable access to sexual and reproductive health information.

CASE STUDY 5

Strengthening SRH knowledge among refugee women in Turkey

I-STOCK/JOEL CARILLET

Context: Refugee women in Turkey face significant challenges to accessing health services and accurate health information due to language barriers, xenophobia and cultural taboos surrounding SRH. These challenges are exacerbated by a lack of health information and education tailored to their cultural and situational needs. An AI-enabled solution is underway that will provide personalized health advice and enhance access to essential health information through WhatsApp, ensuring that everyone, including people with limited digital literacy, can access the bot without downloading additional applications.

Implementation research question: A multidisciplinary team at the Medical Rescue Association of Turkey is exploring the question: How effective is an AI-powered chatbot in increasing SRH knowledge among refugee women?

Research in action: Currently, the chatbot is in the beta access phase, meaning it is open for user interaction and testing. As of November 2024, 110 unique users have initiated 248 conversations with the chatbot. With 41 users returning to ask additional questions, there is strong re-engagement with the tool. A planned advertising campaign is expected to increase user numbers significantly.

Results and Next Steps: : Initial feedback from participants will help evaluate the chatbot's effectiveness in improving SRH knowledge. Following the ad campaign, the project anticipates a rapid growth in user engagement, allowing for quick scaling of the chatbot's reach and impact in similar contexts.

AI approach: Generative AI
AI model: LLM (fine tuning GPT4-o model using Assistant API)
Model maturity: September 2024 (testing and deployment)

Responsible AI: The AI solution prioritizes ethical responsibility and seeks to generate culturally sensitive responses. A no-code panel enables field workers, who are not technical experts in AI, to update information and stay aligned with user needs. Privacy and data security are central, with data anonymized and stored in compliance with the General Data Protection Regulation and the Health Insurance Portability and Accountability Act standards. Feedback monitoring ensures that responses are relevant, unbiased and culturally appropriate.

CASE STUDY 6

Improving maternal care by extending low-resource language datasets across Africa

JJUMBA MARTIN, COO JACARANDA HEALTH

Context: Women in Kenya and other sub-Saharan African countries experience numerous barriers to receiving quality health care due to cultural, socioeconomic and demographic disadvantages. Kenyan-based non-profit Jacaranda Health launched their AI-enabled digital health service PROMPTS to empower new and expecting mothers to seek and connect with the best care via their mobile phone messaging app. The platform uses a customized LLM, UlizaMama (Jacaranda Health, 2023), to provide real-time, personalized support to mothers in Swahili, Sheng or English. The tool has since been expanded into a further five low-resource African languages (Jacaranda Health, 2024).

Implementation research question: A multidisciplinary team is exploring the following question: How can health-seeking behaviours among vulnerable mothers be improved by using an AI-enabled digital health service to detect clinical and socioeconomic risks amongst users and connect them to appropriate care pathways?

Research in action: The team used the Gates Foundation's Pathways segmentation tool to classify PROMPTS mothers within 22 Kenyan counties into vulnerability segments to generate an evidence base for intersectional analysis among underserved women. Beyond basic demographic information, the tool collects valuable information on how education, household headship, religion, the impact of climate events, use of cooking fuel, technology ownership, sanitation and hygiene, age and geolocation create a vulnerability profile. In combination, all these factors influence how women request and respond to health information.

Results and next steps: Initial findings demonstrate that PROMPTS users represent different segments of the general population in Kenya and that each segment has unique health-seeking profiles. For example, more vulnerable segments are willing to enroll on the platform but tend to under-utilize it as a primary resource for their health questions. The research team sees this as an opportunity to dig deeper into health-seeking and engagement drivers with qualitative research to ensure that PROMPTS proactively engages the most vulnerable segments while tailoring support to different socioeconomic needs and experiences among users.

Since its beginnings, almost 3 million mothers have been supported by PROMPTS. The platform is being distributed to mothers in over 1,000 public hospitals and health centres across 23 Kenyan counties. Beyond Kenya, Jacaranda is piloting PROMPTS in Ghana, Nigeria, Eswatini and Nepal, with plans to scale across sub-Saharan Africa over the coming years.

AI approach: Discriminative AI and Generative AI
AI model: Pre-trained transformer multilingual NLP model
Model maturity: 2022 (initial model deployed); December 2023 (UlizaLlama deployed)

Responsible AI: The model is open source to protect user data and reduce risks. The model is hosted, and data is stored on Jacaranda-controlled servers, strengthening oversight on storage and use. Open-source tools limit exposure to changes in model performance and inference costs and allow Jacaranda to modify training protocols to ensure local context and conditions are emphasized to reduce inherent bias that may be present in large, generalized models. All responses over PROMPTS are validated by humans, which allows for contextual modifications of canned responses created by a clinical team. For sensitive topics (miscarriage, severe danger signs, etc.), the human-in-the-loop approach is essential. Finally, user feedback about satisfaction is systematically collected and applied for continuous training and improvement of the model.

Use case 2: Climate change, health and infectious diseases

The intersection of AI with climate and health provides another important use case for consideration because it explores how innovative solutions can tackle the dual crises of climate change and health inequities. The lens of infectious diseases is used to examine how responsible AI can be leveraged to foster resilience and improve health outcomes today and for future generations. The COVID-19 pandemic underscored the need for stronger disease surveillance, the rising influence of zoonosis, the need for more investment in One Health approaches, and the crippling effects on societies when a rapid spread takes place, challenging containment efforts. During the pandemic, AI models played critical roles in genome sequencing, drug and vaccine development, identifying outbreaks, monitoring the spread and tracking viral variants (Parums, 2023). Beyond COVID-19, other infectious disease epidemics are emerging and re-emerging. Most of these can be found in the Global South — Ebola, Dengue and Zika, for example — and merit urgent attention.

Addressing the climate change-related impacts on health relies on data originating from multiple source databases, including health information systems, medical records, early warning systems, logistics systems, financing systems, public health surveillance systems and more. In many countries — both in the Global North and Global South — these systems are challenged by poor coverage, incomplete records, inferior data quality, untimely reporting, limited analysis and use, fragmentation and interoperability issues. Recent advancements in data science and big data analytics allow users to, for example, visualize information and quickly make predictions on an unprecedented scale. By using AI models, new information can be automatically analyzed and provide reliable forecasts (Kong et al., 2023), which can lead to tremendous savings in diagnosis and treatment processes (Khanna et al., 2022).

The case studies, numbered 7 through 11 below, are drawn from ongoing projects funded by IDRC in collaboration with other donors, such as the UK government's Foreign, Commonwealth and Development Office. They have been selected to represent a range of thematic entry points and geographic contexts.

CASE STUDY 7

Mosquito classification in Ghana using AI-enabled acoustics

RAPID VBP-KNUST

Context: Like many tropical countries, Ghana has a high burden of mosquito-borne illnesses. Changes in climate, including increased heat, humidity and heavy rainfall, have led to increased populations of mosquitoes, along with the viruses they carry. Malaria is the most widespread mosquito-borne illness in Ghana. Children under the age of 5 and pregnant women are particularly vulnerable to severe cases of malaria. These cases can lead to reproductive and newborn complications such as anemia, low birth weight, developmental delays and even death.

Implementation research question: A multidisciplinary team at Kwame Nkrumah University of Science and Technology is exploring the question: How can AI tools such as machine learning automatically classify mosquitoes into specific vector species, count their numbers, determine their physiological age, and classify them as potential vectors of novel pathogens?

Research in action: The team has developed and is validating a model to determine its ability to predict mosquito lifespan and behaviours across Ghana. Working closely with communities, the team is classifying mosquitoes based on wingbeat frequency to offer an alternative to traditional morphological and genetic identification methods, enabling early and accurate identification of mosquito species. →

Results and next steps: The team developed a novel, non-invasive and cost-effective AI-driven approach for the early and precise classification of mosquito species. This involved creating an extensive dataset containing 25,344 audio recordings of three key mosquito genera: Aedes, Culex and Anopheles. Leveraging this dataset, a deep learning model was trained to translate wingbeat sounds into images, enabling accurate classification with a 92% success rate. This model is poised to enhance targeted interventions, particularly in regions like Africa, where mosquito-borne diseases are prevalent. Plans are underway across the AI4PEP network to leverage this work for other mosquito-borne diseases in Southeast Asia, South America and the Caribbean.

AI approach: Discriminative AI
AI model: 2D convolutional neural network (CNN), which was developed from scratch
Model maturity: February 2024 (model testing and deployment)

Responsible AI: The project involves diverse stakeholders, including public health experts and community leaders, local health authorities and community members. Inclusive consultations ensure that perspectives from all genders and demographics shape the design and implementation of the surveillance systems, allowing the model to create equitable, accessible solutions that reflect the needs of vulnerable groups and marginalized communities.

CASE STUDY 8

Early warning systems for outbreaks in the Dominican Republic

LEONARDO SANTIAGO

Context: Diseases transmitted by mosquitoes of the genus Aedes cause over 50 million infections and 25,000 deaths worldwide every year. Climate change has exacerbated this issue as the mosquitoes and the pathogens they transmit reach more countries. Dengue, chikungunya and Zika are endemic diseases in the Dominican Republic. The country reports an average of 10,000 dengue cases annually and has seen over 5,200 cases of chikungunya and 700 cases of Zika during major outbreaks in the past decade. As an island nation, the Dominican Republic is one of the most vulnerable to climate change globally, with rising temperatures, increased rainfall, and humidity creating ideal conditions for Aedes mosquitoes. This highlights the urgent need for action to address these challenges.

Implementation research question: A multidisciplinary team at the Health Research Institute of the Universidad Autónoma de Santo Domingo (UASD), is investigating the research question: How can a community-based and policy-relevant early warning system leverage AI responsibly toward integrating epidemiological, meteorological, entomological and other data to issue alerts when an outbreak is imminent or ongoing?

Research in action: The team is developing an integrated system with four core elements:

- Assessment and understanding of outbreak risks
- Hazard surveillance, forecasting and alert services
- Risk communication and dissemination
- Response capacity →

The system includes innovative tools, such as customized chatbots and deep learning-based models to support the dissemination of information in local communities. These tools aim not only to predict outbreaks with high precision but also to educate the population on effective preventive practices. The approach includes assessing flood risks, monitoring hazard factors and engaging proactively with communities to enhance their response capacity.

Results and next steps: Pilot tests will be implemented in communities to evaluate its real-time effectiveness. Once validated, this system has the potential to optimize public health interventions in the country, enabling a faster and more efficient response to outbreaks. In the long term, the results are expected to serve as a foundation for scaling these solutions regionally and globally in countries facing similar challenges.

AI approach: Discriminative AI
AI model: Convolutional neural network adapted to multivariable data
Model maturity: November 2022 (model development and testing)

Responsible AI: The project involves community leaders, local authorities, public health experts and non-governmental organizations. Inclusive consultations ensure that the tools developed address the real needs of communities and promote equity in access to health information and services.

CASE STUDY 9

CENTER FOR TROPICAL MEDICINE, UNIVERSITAS GADJAH MADA, INDONESIA

Intelligent early warning and response system to improve national health resilience in Indonesia

Context: Located in the equatorial line, Indonesia is exposed to various arbovirus infectious diseases such as dengue, malaria and Zika. Dengue poses a significant burden nationally, estimated at US$385 million annually (Nadjib et al., 2019). Limited healthcare resources, ineffective public health messaging and a shortage of trained epidemiological personnel, especially in rural and remote areas, contribute to the poor control of this disease. Although Indonesia has implemented an early warning alert and response system based on syndromic surveillance (to track possible outbreaks) reported by healthcare facilities since 2009, its effectiveness is still limited.

Implementation research question: A multidisciplinary team from the Center for Tropical Medicine at the Faculty of Medicine, Public Health, and Nursing at the Universitas Gadjah Mada in Yogyakarta aimed to address the question: How can health disparities caused by disease outbreaks be redressed using responsible AI models (combining health systems routine data and environmental data) to enhance prediction and prevent future public health crises?

Research in action: The team reviewed infectious disease surveillance systems and conducted several focus groups with the Ministry of Health and Provincial Health Office in Yogyakarta, one of the largest regions in Indonesia with problems in controlling dengue infections. An AI solution is being developed by working closely with the Ministry of Health and Disease Control and Prevention in the Provincial Health Office. →

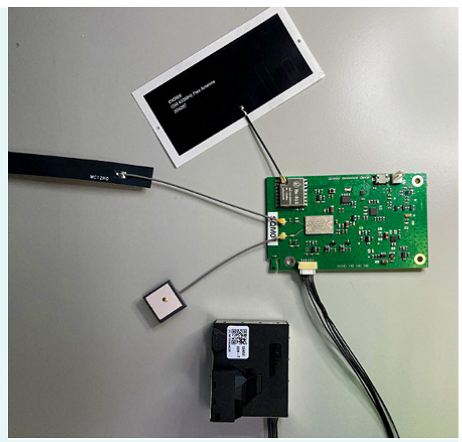
Results and next steps: An AI-enabled prediction model is under development and validation. It is designed to predict the number of people with dengue and dengue outbreaks based on environmental data and online consultation. The team is developing a solution to ensure the quality of syndromic disease surveillance data collected at the healthcare facility level using LLM from electronic medical records data.

AI approach: Discriminative AI
AI model: Statistical learning methods such as regression, tree-based and neural-network-based models such as XGBoost and graph neural network (GNN)
Model maturity: Development and validation stage

Responsible AI: : The team actively involves stakeholders throughout the process to identify key issues that should be addressed to ensure the AI system aligns with the needs and values of those it impacts. By fostering collaboration and emphasizing transparency, the AI-enabled solution is technically robust, ethically sound and socially beneficial.

CASE STUDY 10

Scaling local innovations in South Africa for enhanced air pollution monitoring



SOUTH AFRICAN CONSORTIUM OF AIR QUALITY MONITORING

Context: Poor air quality has emerged as a major public health challenge globally. Nearly 99% of the world's population breathes air that exceeds WHO's guideline levels (WHO, 2024b and 2024c). In fact, poor air quality is now responsible for more deaths across the African continent than the combined death toll of HIV, malaria and TB (Fuller et al., 2022). Poor air quality results from environmental and human-generated activities and compromises the health and productivity of individuals and entire communities. Community-based solutions that examine human and environmental behaviours can help raise awareness of air pollution hotspots and lead to more tailored solutions to address the root causes.

Implementation research questions: A multidisciplinary team at Wits University and iThemba LABS in South Africa is seeking evidence for the questions: How can the deployment of a large-scale AI-powered air quality monitoring network improve the coverage and reliability of air quality predictions? What are the most effective strategies for integrating real-time air quality data with public health interventions to reduce the incidence of respiratory, cardiovascular and other diseases?

Research in action: Working with public and private sector actors, the team established a cost-effective, high-quality network of AI-enabled sensors across Gauteng province. The AI_r project leverages South African expertise to develop boxes at a cost of about US$100 each. Mounted on windowsills to capture data, these devices use limited amounts of electricity and can withstand various weather conditions. Each box shoots a laser into the air, measuring how the light scatters based on the concentration of particulates. The large dataset is then analyzed and visualized on dashboards using AI solutions. The first 30 devices were placed in Soweto, Braamfontein, Johannesburg and Kya Sands, with an additional 120 devices to be installed around Gauteng by 2025. This will be the largest and most cost-effective air quality network in Africa. →

Results and next steps: The AI-based system includes a dashboard for real-time air quality monitoring, which feeds into the South African Air Quality Information System (SAAQIS). The team delivered the dashboard with data captured from 30 sensors in Soweto schools, Wits University, iThemba LABS and the Milkpark Netcare Hospital. Sensors collected data through the winter when air quality is the poorest, representing a major milestone that demonstrates the technology's robustness to run over long periods and in difficult weather conditions. Other provinces in South Africa are growing interested in using similar sensors to monitor air pollution and detect hotspots. The project has secured an agreement with a leading Internet Service Provider in South Africa to leverage their infrastructure to deploy AI_r sensors nationwide. The AI_r project is working successfully with government and private sector partners to expand the reach of real-time air quality monitoring through sustained community involvement, reliable power supply, enhanced security and protection, and strong buy-in and support from government bodies.

AI approach: Generative AI and discriminative AI
AI model: RNN, DNN, GNN, CNN, GRU, BERT and Foundation models
Model maturity: November 2022 (model testing); September 2023 (deployment)

Responsible AI: Responsible AI in the context of air quality monitoring requires the data and modelling results to be publicly available. This compels experts to ensure that algorithms and outcomes are explainable, despite the complex math that underpins ML. Engagement with communities through lightweight graphical interfaces and apps is pivotal in conveying AI's practical outcomes and benefits to communities and policymakers for communities affected by poor air quality.

CASE STUDY 11

Tackling waterborne pathogen (re)emergence in Tunisia

DIRECTORATE OF ENVIRONMENTAL HYGIENE AND ENVIRONMENTAL PROTECTION, MINISTRY OF HEALTH, TUNISIA

Context: In water-stressed regions such as Tunisia, there is an urgent need to reuse water, including treated wastewater, for irrigation in agriculture. With this reuse solution comes the risk of pathogen transmission into the food system, including drug-resistant bacteria, viruses, parasites and fungi. Addressing gaps and challenges in pathogen surveillance and antimicrobial resistance (AMR) is critical. Unfortunately, there is a lack of understanding regarding current trends in those pathogens and AMR in Tunisia, despite several pathogens, including salmonella, being detected in treated wastewater in various regions.

Implementation research question: A multidisciplinary team at the Institut Pasteur de Tunis, in close partnership with the Ministry of Health, is investigating the following questions: How can responsible AI be integrated with wastewater quality surveillance to enhance the monitoring, predictions and early warning of outbreaks? How can the AI-enabled analysis provide actionable recommendations for effective control strategies to mitigate the spread of pathogens and AMR? →

Research in action: The team digitized and analyzed extensive wastewater data from 2017 to 2024, spanning 21 treatment plants in rural and urban areas across Tunisia. They launched a biannual sampling campaign (2025–2028) in collaboration with the Ministry of Health to monitor high-priority pathogens — including bacteria, viruses and parasites — and AMR markers. The data feeds into the AI-powered dashboard, a pioneering tool for tracking pathogen trends, salmonella serovars diversity and antibiotic resistance. The dashboard is available to the government, policymakers and researchers.

Results and next steps: The AI-enabled dashboard is the first of its kind dedicated to waterborne pathogen surveillance in Tunisia. The project successfully identified and prioritized a list of pathogens based on epidemiological and environmental data, including vibrio and salmonella, hepatitis A and E, poliovirus and microsporidia. The AI-powered dashboard is undergoing review and will be made available for widespread use by the government, allowing them to visualize historic data and predict wastewater disease outbreaks. Over the next four years, the project will integrate prospective pathogen and AMR data from the wet and dry seasons to launch a repository website. They will develop predictive models using environmental, community and demographic data for risk assessment in a dashboard.

AI approach: Discriminative AI
AI model: Deep neural networks
Model maturity: Development phase

Responsible AI: The AI model being designed is ethical, transparent and inclusive through its co-creation process and the creation of risk maps to guide equitable resource allocation. The selection of wastewater treatment plants across Tunisia was done intentionally to avoid biases toward larger cities or coastal towns. This is particularly important as these latter areas face a noticeable rise in social demands, especially in marginalized communities.

The case studies in this section represent a small subset of the many different entry points and manifestations of leveraging responsible AI solutions across the health system and health-adjacent systems. Recognizing the vast array of applications of responsible AI solutions to advance global health objectives, this paper contends that some core knowledge gaps, approaches, cross-cutting considerations and analytical lenses can be articulated to begin mapping out an emergent research landscape.

Knowledge gaps and related evidence needs

AI solutions alone will not magically solve the deeply entrenched, historically rooted and contextually specific global health challenges. In fact, they can exacerbate existing digital, health and other types of inequalities (van Kessel et al., 2022; Khosla et al., 2023).

As researchers and innovators continue to explore the use of AI in global health, there are knowledge gaps to address, evidence needs to fill, and locally championed and implemented research agendas to define, refine and deliver on. Defining an authoritative research agenda is not the purpose of this paper. On the contrary, this paper foregrounds the paramount importance of Global South vision, wisdom, leadership and follow-through on defining and delivering a contextually relevant and scientifically rigorous research agenda for responsible AI and global health. The next section proposes an emergent research landscape to facilitate the process of filling pressing knowledge gaps with locally relevant and locally championed research conducted in the Global South.

Responsible AI and global health

An emergent research landscape

I-STOCK

Prioritizing investment in research to improve health and wellbeing is predominantly influenced by individuals and institutions that hold the most power (Birn, 2014). Illnesses that place an immense burden on communities and health services across the Global South are not generally prioritized in the northern-dominated AI value chain (de Souza Rodrigues et al., 2024). As a result, neglected and marginalized conditions such as TB, Chagas, polio, dengue fever, malaria and mental health can become further sidelined in AI research and development. For example, the development of innovative AI solutions to improve health outcomes for individuals and populations across the Global South continues to ignore pressing challenges such as poor air quality, water scarcity and antimicrobial resistance (Ueda et al., 2024).

Advancing the current state of AI and global health research requires addressing knowledge gaps, identifying evidence needs and bringing a Global South perspective to the forefront. With a fast-moving field like AI and the 2030 deadline to meet the SDG targets, this research landscape is designed to plant the seeds for longer-term research agenda discussions.[3]

Developed through extensive literature reviews, analysis of existing projects and a series of 17 key informant interviews, the proposed emergent research landscape is a starting point for discussions, exploration and experimentation, with a view to putting the spotlight on the overarching trends, considerations, analytical lenses, possible entry points for research and elements needed for stronger and more resilient health systems to flourish.

> *Advancing the current state of AI and global health research requires addressing knowledge gaps, identifying evidence needs and bringing a Global South perspective to the forefront.*

What research is needed?

Alongside the growing body of evidence acknowledging the potential of AI solutions to improve health outcomes, there is a call among researchers for more evidence on how AI solutions are helping to reduce health disparities and different forms of injustices (Dankwa-Mullan et al., 2021; Berdahl et al., 2023; van Kessel et al., 2022). Filling knowledge gaps on if, how, for whom and in what contexts responsible AI solutions are improving health outcomes, redressing health inequities and strengthening health systems requires interdisciplinary and intersectoral approaches that address the root drivers of health inequity and strained health systems. Moreover, greater representation of scholarship from individuals and institutions based in the Global South will enrich the value and relevance of evidence that speaks to these contexts (Kong et al., 2023; Reddy et al., 2021).

While there are parallels with the digital health research landscape, there are specificities around the use of responsible AI for global health that arguably merit a focused approach. For example, the complex and opaque nature of many algorithms used within AI solutions lends itself to a dedicated research approach (Schwalbe & Wahl, 2020).

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[3] Although "research framework," "research agenda" and "research landscape" are related terms, this paper intentionally uses the term "research landscape" because it encompasses the broader context of trends, existing research and gaps in the field without being overly prescriptive or rigid.

Other traits and specificities of AI that lend themselves to a dedicated research landscape include:

TRAIT/FEATURE	DESCRIPTION
Scale	AI solutions are often referred to as inherently scaled phenomena because their effectiveness tends to increase with a greater scale of data, computing power and model complexity.
Ubiquity	The use of AI across all sectors and for a range of functions, often in ways that are not visible or known to the end-user, has a widespread influence on how people access health care, learn, work, communicate, shop, travel and make decisions in their daily lives.
Conversational	The ability of an AI-enabled system to engage in human-like dialogues with users through text or voice. Trained to understand, process and respond in ways that are natural and empathetic, the conversational feature of AI significantly reduces the need for "expert knowledge" to access information and knowledge.
Generative	The capacity of generative AI to create new multimodal content quickly sets it apart from previous digital technology. This is because the latter uses rule-based operations and explicit instructions, whereas the former learns from data to produce outputs that reach beyond predefined commands.
Rapid pace of AI design and compute	The rapid evolution of AI design and compute is driven by the exponential growth in computing power, breakthroughs in model architectures like deep learning and transformers, the availability of large datasets, and the rise of open-source tools and collaboration.
Pace of adoption	The ubiquity and accessibility of AI have led to a rapid pace of adoption without clear metrics (or accountability measures) for success and failure.
Nascent regulatory and governance frameworks	Operating without robust, effective, transparent, comprehensive, accountable and evidence-based guardrails for responsible AI is a shared concern. Existing regulatory frameworks and enforcement mechanisms are not sufficiently developed or tested to ensure safety and protect rights.
Positioning and role of humans	Focused attention on the nature of and extent to which "humans are in the loop" for AI solutions to optimize decision-making, minimize errors and inject higher levels of ethical standards is heightened when compared to other digital technology solutions.

Implementation research to "ground truth" in responsible AI solutions

The emergent research landscape presented in Figure 1 contains elements to ground the research in relevant contextual trends, while providing parameters and filters to articulate features that warrant attention on the responsible AI and global health research landscape. The complexities and implications at the crossroads of AI and global health require a multifaceted approach to research at this critical juncture. Calls for more context-specific research that examines real-world applications of AI solutions to advance global health are growing — including a response to the spread of generative AI-based solutions (Reddy, 2024; Reddy et al., 2021).

For the purposes of the emergent research landscape, implementation research has been adopted as the lens through which to frame how knowledge gaps could be addressed.
Implementation research is an integrated approach designed to bridge the gap between what is expected to happen when promising AI solutions are designed and what actually happens when they are implemented in real-world settings. This delta between what is known about an intervention, how it should unfold and how it unfolds as it interfaces with different contextual factors in the real world is called the "know-do gap."

In the AI and global health context, implementation research will aim to address this gap by looking at AI solutions designed to improve clinical and public health outcomes. The research will seek to understand how and why interventions work in the real world and test approaches to improve them (Peters et al., 2013). Implementation research can also be applied to less tangible processes such as policymaking.

The difference between implementation outcomes for health research and health outcomes

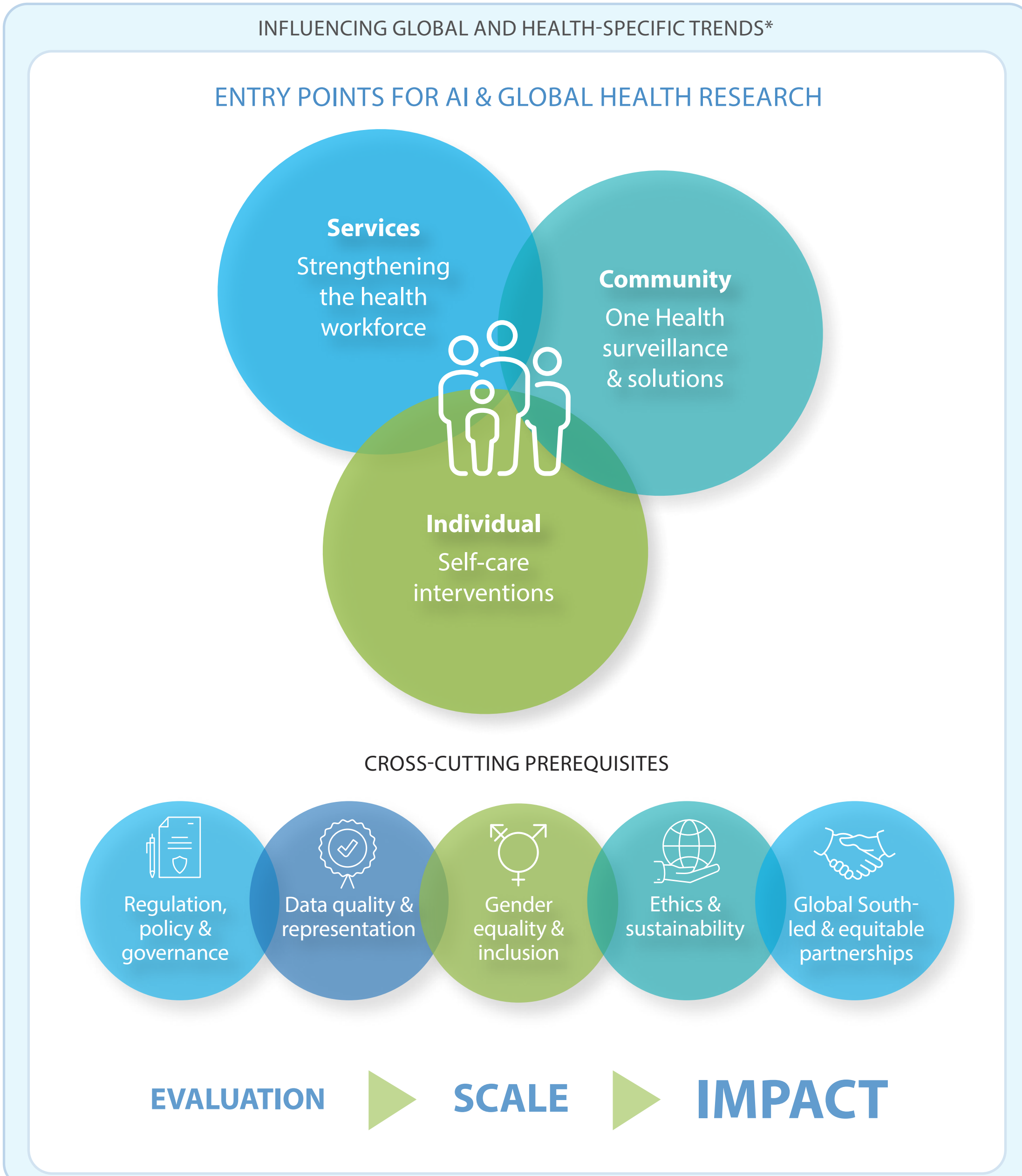
Implementation outcomes measure the success (or failure) of an intervention. This can include, for example, acceptability, adoption, appropriateness, feasibility, fidelity, cost, coverage and sustainability of an intervention.

Health outcomes measure changes in health status, such as mortality, morbidity, quality of life, disability-adjusted life years, satisfaction with care or effectiveness of care.

Both implementation and health outcomes are important to measure when conducting research because they allow for lessons on the implementation process and its impact on health. One should not come at the expense of the other. It is best to look for linkages between implementation and health outcomes to help refine an intervention and advance implementation strategies which aim to improve health outcomes.

This paper promotes a research landscape that begins with an implementation research approach toward measuring implementation and health outcomes. When championed by local researchers, such an approach attempts to allay challenges around the intentional or unintentional application of colonial practices and evidence that is not useful or relevant to the local context.

Figure 1: **Emergent research landscape for responsible AI and global health**



* ***Global:*** *Polycrisis, growth in computational power, big data, use of AI (specifically ML), emergence of generative AI, mis- and disinformation, pushback on social and gender rights, concentration of power and wealth, gender-based violence, emerging and exisiting conflicts, mass displacement, climate crisis.* ***Health-specific:*** *Strained health systems, digital health (including AI), self-care, preventative care, mental health, adolescent health, sexual and reproductive rights, antimicrobial resistance, vaccination acceptance and coverage, global health security, chronic disease, malnutrition and obesity, emerging and re-emerging infectious diseases, zoonoses, water sanitation and hygiene, air pollution.*

Global and health-specific trends

Research requires political, social and cultural context to ground it. Otherwise, it is limited in its use and arguably challenged ethically (Longino, 1990). Research on global health conducted in the Global South requires context-specific insights; without them, the research may be ineffective even if it is scientifically sound (Peters et al., 2013).

The backdrop against which AI and global health research takes place features a wide range of influencing global and health-specific trends. These are dynamic, evolving issues and challenges that impact the research environment and should be considered in developing AI solutions for global health. These trends are listed at the bottom of Figure 1.

The starting point: Neglected populations and conditions

As AI solutions grow in number and sophistication, their availability and relevance can be limited to a small subset of the population. This is an example of health data poverty, defined as the "inability for individuals, groups or populations to benefit from a discovery or innovation due to a scarcity of data that are adequately representative" (Ibrahim et al., 2021). Unless this health data poverty is reversed, large populations — often those already experiencing the deepest vulnerability and deprivation — will continue to be invisible or under-represented in health datasets.

This paper contends that it is crucial to look at the most underserved populations (those facing the most heightened and complex intersection of vulnerabilities) and neglected conditions (those that attract meagre investment and interest). Neglected populations include women, youth, displaced people, Indigenous groups, ethnic minorities, persons living with disabilities, slum dwellers, and sexual and gender minorities. Many of these groups overlap.

The rationale behind setting neglected populations and conditions as the starting point for this emergent research landscape is an attempt to recalibrate attention away from populations who are more advantaged and generally benefit from greater investments in health conditions they experience toward an approach that seeks to address health conditions affecting large portions of the populations who have relatively less power and influence over the global health research agenda. In doing so, this approach is intentional about minimizing risks and explicit about reducing gender inequality and various forms of exclusion. Ultimately, this approach will allow researchers to contribute to analyzing, testing and developing AI solutions that can support health and wellbeing for all, starting with the most vulnerable groups and neglected conditions.

CASE STUDY 12

Deep learning for community-based surveillance of acute flaccid paralysis in Ethiopia

Context: Polio remains a concern in several countries, including Ethiopia. With most polio cases affecting children under 5, early identification of the virus is the first step toward eradication of a disease that can lead to lifelong disabilities. Acute flaccid paralysis (AFP), characterized by rapid onset of muscle weakness or paralysis, is a hallmark symptom of polio. Monitoring AFP in remote areas faces significant barriers, including insufficient healthcare infrastructure, inadequate transportation and communication, high population mobility, security challenges, cultural and linguistic diversity, and low community awareness. These factors contribute to underreporting and delays in case detection. A potential solution lies in an AI-enabled LMM that enables timely AFP surveillance.

Implementation research question: A multidisciplinary team at Jimma University is exploring the question: Can an AI-powered platform that utilizes image data collected through the mobile phones of community volunteers enhance the efficiency of AFP surveillance? →

Research in action: The team developed the first deep learning-based transfer learning model in the world for identifying AFP cases collected by community volunteers. The AI model is integrated into a mobile app called PolioAntenna, which is currently used by government, communities and non-governmental organizations (NGOs) in Ethiopia.

The model uses a local dataset of 428 images, comprising 228 suspected AFP cases and 200 normal cases, collected from Ethiopian children over the past five years. They represent 82 rural pastoralists and hard-to-reach districts (called Woredas) located in six regional states: Benishangul-Gumuz, Gambella, Oromia, Somali, Southern Ethiopia and Southwest Ethiopia. The repository is unique in its ability to capture AFP surveillance data, in text form and image format, automating decision-making and enabling AI models to be trained on it.

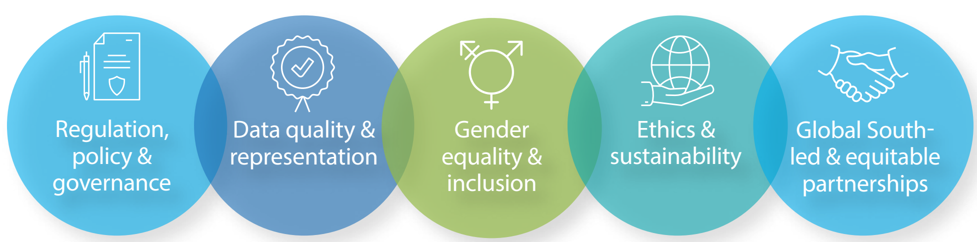
Results and next steps: The deployment and uptake of the AI-enabled solution in different *Woredas* across Ethiopia marks an important step toward closing gaps in community-based surveillance for a rare disease. This study offers a scalable and sustainable solution for enhancing disease surveillance and control, from community-based reporting to health facility and district-level systems. Establishing a dedicated platform for data storage and analysis ensures the preservation of valuable information for future learning and preparedness, facilitating more effective responses to public health threats. There are promising signals for the team to implement the tool across other *Woredas* and expand their impact across Africa with reported poliovirus cases.

AI approach: Discriminative and generative AI
AI model: Deep learning, transfer learning, pre-trained vision transformer model with updated additional layers
Model maturity: September 2024 (pilot deployment)

Responsible AI: The project involves public health experts and community volunteers, traditional healers, educators, clergymen, birth attendants, leaders of women's groups, youth, bonesetters, local health authorities, regional health bureaus, Ministry of Health, Ethiopian Public Health Institute, WHO, UNICEF, NGOs and funding partners. Inclusive consultations ensure that perspectives from all genders and demographics shape the design and implementation of the surveillance systems, allowing the model to create equitable, accessible solutions that reflect the needs of vulnerable groups and marginalized communities.

Cross-cutting prerequisites

The emergent research landscape in Figure 1 proposes five cross-cutting prerequisites that should be adequately addressed in research designs and implementation strategies — regardless of the health entry point, population(s) of interest or intended outcomes.



Each prerequisite calls for careful attention at the design stage of a research project. It is equally important to revisit the analytical lenses and make course corrections throughout the lifecycle of an AI and global health project. Although presented separately, there is considerable overlap across many of the considerations. Moreover, the order in which these are presented in this paper does not imply relative priority or sequencing in practice.

Regulation, policy and governance

Regulation, policy and governance are essential and interrelated components in the development and deployment of responsible AI. WHO emphasizes the importance of these three considerations to ensure the safe, ethical and effective use of AI in health care (WHO, 2021a). The rapid pace and evolving nature of AI technologies underline the urgency to find the delicate balance between fostering innovation and maintaining regulatory compliance that strengthens safety and protects rights (Walter, 2023).

Although most countries lack dedicated AI legislation for health, AI applications are often regulated under the broader category of medical device regulations or software as a medical device (HealthAI, 2024). This provides a strong foundation but does not provide sufficient regulatory oversight for all forms of AI use in health. Moreover, the cross-border nature of global phenomena and the flow of data merit discussions about AI regulation, policy and governance at the national and international levels (Zaidan & Ibrahim, 2024). Despite the limited number of national AI policies developed and enforced across the Global South, the proliferation of AI solutions in health continues to flourish with little or no policy or regulatory oversight (WHO, 2024). Examining the regulatory environment for AI in health care across the globe — including several countries in the Global South — the landscape reveals significant gaps that render current standards, guidelines and enforcement insufficient to address the unique aspects of AI (HealthAI, 2024; Van Laere et al., 2022). Alongside innovative AI solutions and applications, there is a need for commensurate policy and regulatory measures.

> *The rapid pace and evolving nature of AI technologies underline the urgency to find the delicate balance between fostering innovation and maintaining regulatory compliance...*

Countries with national AI policies as of December 2024

REGION	COUNTRY
Asia	China, India, Indonesia, Japan, Russia, Singapore, South Korea, Taiwan, Thailand and Vietnam
Europe	Austria, Belgium, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Slovenia, Spain, Sweden, Switzerland and the United Kingdom
Latin America and the Caribbean	Argentina, Brazil, Chile, Colombia, Mexico, Peru and Uruguay
Middle East and North Africa	Egypt, Qatar, Saudi Arabia, Tunisia, Turkey and United Arab Emirates (UAE)
North America	Canada and the United States
Oceania	Australia and New Zealand
Sub-Saharan Africa	Benin, Ghana, Kenya, Mauritius, Rwanda, Senegal, Sierra Leone and South Africa. There is also a regional AI strategy, The African Union Continental AI Strategy.

Source: OECD.AI Policy Observatory

Robust regulatory, policy and governance structures and processes provide frameworks for accountability, privacy protection and equitable access. Moreover, they help prevent misuse and ensure AI innovations contribute positively to global health outcomes. When exploring implementation research projects to leverage responsible AI solutions to strengthen health outcomes and health systems across the Global South, some issues to consider include:

Regulation, policy and governance
Examine the existence of data protection laws that govern how personal health data can be collected, stored and used, as well as compliance with such laws.
Strengthen regulations that ensure AI systems are transparent and explainable in their decision-making processes within health systems.
Generating clinical evidence demonstrating the safety and effectiveness of different AI-enabled tools.
Explore clear lines of responsibility and accountability for AI-enabled decisions in health systems. Doing so can strengthen the ability of individual citizens and communities to hold AI solution developers, health providers, institutions or others accountable.
Propose ethical and other guidelines on how to ensure an augmented intelligence approach, which requires human oversight in critical decision-making processes.
Research pricing regulations to promote greater accessibility and affordability for high-quality AI solutions, particularly for the Global South and low-resource languages.[4]
Promote collaborative approaches to greater AI interoperability standards that are compatible with existing global standards but start from a Global South vantage point.

Data quality and representation

Data has been referred to as the new gold, new oil, new currency and a range of other terms that underscore its indisputable importance and value in shaping perceptions, policies and practices in nearly all aspects of life. Strengthening health systems and achieving the SDGs by 2030 relies on robust and reliable data, information systems and data science, including the use of AI solutions (Bachmann et al., 2022; Palomares et al., 2021).

High-quality, representative and disaggregated data is the foundation of any responsible AI system that aims to address diverse unmet needs among different populations experiencing intersecting vulnerabilities. Poor quality data can suffer from challenges of under-representation, misrepresentation and over-representation. Each of these can lead to biases — such as selection bias, exclusion bias and detection bias, among others — in how AI solutions are trained and the results produced by their algorithms (Ntoutsi et al., 2020). This points to the important role of strong data structures and data science in supporting AI-enabled solutions to draw from well-governed, appropriately stored and securely shared data (Panch et al., 2019).

[4] Low-resource languages can be described as languages that lack digital linguistic resources, including insufficient data for training AI models, the performance of LLMs is frequently subpar (Dash, 2022).

AI inherently involves data limitations that lead to bias (Obermeyer et al., 2019). Undesirable biases in AI solutions can influence and be mirrored throughout the entire design, development and deployment cycle. For example, a study examining bias in AI-enabled medical imaging identified 29 different biases across five different stages: data collection, data preparation, model development, model evaluation and model deployment (Drukker et al., 2023). It is not possible to fully remove bias from AI solutions; rather, robust mechanisms to detect and minimize these biases are essential to ensuring fairer and more equitable outcomes. Moreover, utilizing an augmented intelligence or human-in-the-loop approach ensures that AI-enabled processes remain under informed human oversight.

The reality of LLMs is that they can be a double-edged sword. They can provide unparalleled access to personalized responses, but their vault of knowledge and accuracy of responses will vary significantly across different languages, population groups and health conditions. For example, the training dataset for the open-source LLM LLaMA2 is 89.7% in English; however, a low-resource language such as Vietnamese accounts for only 0.08% of the training dataset content (Touvron et al., 2023). Some specific issues to consider in improving data quality and representation include:

Data quality and representation
Strengthen ontologies that can help ensure data triangulation and analysis are robust and meaningful.
Ensure data is structured for secure interoperability.
Measure the availability and reliability of local datasets to address health needs and capture groups that are most impacted.
Explore how cross-jurisdictional (including cross-border) data sharing can be done in ways that are aligned with sound data science and data governance practices.
Generate and test robust and relevant models (including Indigenous models) to protect and govern health data that adheres to global standards and local contexts.

Gender equality and inclusion

Differences in health outcomes between women, men and gender-diverse individuals are related to biological, social, cultural and political factors. Marginalized and disadvantaged groups are consistently exposed to health risks; they are less likely to seek health care, receive lower-quality health services and experience poorer health outcomes (Whitehead, 2006). Gender identity, roles, relationships and norms influence how individuals and groups access reliable health information and quality health services.

The heightened use of AI solutions can perpetuate and amplify coded inequity, meaning the individuals who design and adopt AI tools do not think carefully about different forms of systemic oppression and exclusion (Benjamin, 2019). If left unchecked, the design and deployment of AI solutions will inevitably be shaped by powerful groups and the dominant social and gender norms these groups tend to align with, leading to intentional, unintentional, visible or invisible forms of discrimination.

More robust and inclusive gender-disaggregated data will strengthen the ability to count, measure and respond to the health needs of those previously not counted or not visible in the datasets. There is a need for continued efforts to diversify the pool of local talent that designs, uses and interprets AI-enabled global health solutions toward better representation across all parts of the AI and global health ecosystem of actors.

All responsible AI solutions and related research must include a robust and locally relevant analysis of gender equality and inclusion. This approach should adopt an intersectional lens, which involves examining how social categories such as gender, age, class, sexual orientation, race, disability, religion, citizenship, migration status and other factors lead to mutually constituted and overlapping privileges or oppressions that are dynamic rather than operating in isolation from one another (Larson et al., 2016). Some specific issues to consider toward improving gender equality and inclusion include::

Gender equality and inclusion
Consider issues of access to devices, connectivity and other necessary resources for leveraging AI solutions.
Understand how prevailing social and gender norms influence AI regulations, AI solutions, health providers, health-seeking behaviours and more.
Research data bias and the underrepresentation of certain groups.
Focus AI solution design and purpose to address various disabilities.
Explore the implications of underrepresentation in diagnosis and treatment, including areas like medical countermeasures and medical supplies.
Use responsible AI solutions to address bias in clinical trials and address sex-specific issues (for example, endometriosis and maternal mental health).
Diversify the pool of locally trained talent that design, deploy, use and apply results from AI-enabled solutions. This ranges from computer scientists, social scientists, data scientists, health workers and health decision makers.

Ethics and sustainability

In recent years, researchers have explored the importance of ethics when developing, using and regulating AI solutions in health care (Li et al., 2022; Morley et al., 2020; Morley et al., 2019). This body of knowledge focuses predominantly on clinical settings in the Global North and pays limited attention to public and population health considerations (Murphy et al., 2021). The WHO (2024) established six core ethical principles for using AI, notably to:

1) Protect human autonomy
2) Promote human wellbeing, safety and the public interest
3) Ensure transparency, explainability and intelligibility
4) Foster responsibility and accountability
5) Ensure inclusiveness and equity
6) Promote responsive and sustainable AI

As data becomes more disaggregated and granular, which subsequently feeds AI solutions, the need to protect the privacy of individuals and groups is further heightened. A growing number of cases has been documented where individual-level data is used for different purposes, pointing to the importance of balancing the benefits of this data and minimizing the harm resulting from its malicious or inadvertent release and use (Ragin et al., 2019; Beck et al., 2016).

As with other technologies, such as proven vaccines, ethical dilemmas can emerge both when applying technology and when withholding it. Failure to address ethical dilemmas may increase harm, reduce inequalities and fail to optimize just benefits for populations experiencing the most unmet health needs.

All responsible AI solutions and related research should examine ethical principles and practices alongside processes to enhance social, economic, environmental, political and technological sustainability. Some issues to consider toward these ends include:

Ethics and sustainability
Align AI solutions — from design to implementation and assessment — with human rights principles.
Minimize bias to ensure more fair treatment across different user groups.
Find ways to ensure AI models are more transparent, explainable and interpretable.
Explore the appropriate balance between human control and machine autonomy.
Limit privacy violations and improve data security.
Explore models to reduce waste and the environmental impact of AI.
Price AI solutions, such as LLMs, so they are affordable for populations most in need and with limited financial resources.

Global South-led and equitable partnerships

Global South leadership and equitable partnerships are two separate but deeply connected approaches. Strong and sustained research leadership from the Global South, including generating locally relevant evidence translated into policy and practice, is a critical and requisite component for strong, fair and resilient health research systems (Abouzeid et al., 2022).

Global South-led research leadership is part of a broader effort toward equitable partnerships across research teams, funders, journals and other actors shaping the research and evidence landscape. A focus on leadership from the Global South is essential to ensure that deep contextual understanding, local expertise, and strong connections to communities and decision-makers at different levels are strengthened and leveraged (Bhakuni & Abimbola, 2021). Beyond rectifying the imbalance in scholarship led by Global South leaders, addressing the different barriers faced by researchers based in the Global South also requires examining disparities within groups (Gonzalez-Alcaide et al., 2017). These include the continued underrepresentation of women as lead authors and in global health leadership positions (Merriman et al., 2021).

There is also a pressing need for research funders to address imbalances in power and resources between researchers in the Global North versus those in the Global South (Charani et al., 2022). This approach does not preclude engaging individuals or institutions from outside the local context; however, the decision to do so — and the nature of any collaboration — should be driven by locally based researchers and implementers. Equitable partnerships are those that are ethical, respectful and equitable with regard to the distribution of power and resources (Charani et al., 2022; Boum et al., 2018).

The value of co-creation and Global South leadership could not be more fitting for the current AI and global health environment. The stakes are high, and the fallout of being excluded from discussions related to governing and regulating AI would be borne disproportionately by individuals experiencing the deepest forms of intersecting inequalities across the Global South.

Some issues to consider when striving for more Global South-led and equitable partnerships include:

Global South-led and equitable partnerships
Adopt an ecosystem approach to strengthen existing and seed emerging research capacities across the Global South (which is not homogenous and includes great variety).
Prioritize efforts that Global South-based organizations champion.
In organizations, include leadership and broad membership from women and other historically underrepresented groups within the specific society.
Ensure the principles of equitable partnerships are practiced when multiple partners are involved from across the Global South and beyond.
Support evidence published with lead authorship from individuals based in institutions across the Global South.
Facilitate the participation of Global South researchers in conferences and events in the Global North to ensure their voices are heard and to seed equitable partnerships.

Three indicative entry points for AI and global health research

Based on the literature review, project analysis and key informant interviews, three indicative research areas are proposed along three interconnected categories: 1) health services, 2) community health and 3) individual health. These three areas build on the evidence review and case studies emerging from the two use cases presented earlier. Although these areas are presented separately, the diagram illustrates how they intersect with one another. Moreover, the description for each of the three areas was intentionally non-prescriptive to leave space for debate and refinement.

Health services: Strengthening the health workforce

The health workforce represents one of the six building blocks for health systems. Each of the building blocks relies on one another, with strengths and weaknesses having spillover effects on other building blocks and the health system as a whole (WHO, 2007; Mutale et al., 2013). As the human face of health systems and as the users of AI in health service delivery, selecting the health workforce pillar as an indicative area for implementation research provides an opportunity to examine the critical role of frontline health workers in using AI when interacting with individuals seeking information or services for preventative or curative health needs (Billings et al., 2021).

In most health systems, both across the globe and especially in resource-constrained parts of the Global South, there is a severe shortage of qualified frontline health workers (Naal et al., 2020). Over 70% of frontline health workers worldwide are female, and many face multiple barriers to accessing training, leadership opportunities and fair compensation (Blau et al., 2021; Naal et al., 2024). These individuals are often the first point of contact for patients, whether at a hospital, community clinic or home visit. The essential role of frontline health workers becomes more evident during times of crisis, such as disease outbreaks and other crises (Okoroafor et al., 2022). This spike in the urgent need for skilled frontline health workers is called surge capacity (Gupta et al., 2021).

Lessons from COVID-19 and other epidemics have shown the importance of addressing the different needs of frontline health workers to ensure they have access to relevant skills, supports and reprieve from anxiety and stress (Dugani et al., 2018). Building an evidence base on how gender-responsive and responsible AI solutions can support frontline workers is essential to responding to existing demands and surge capacity, while proactively preparing for the future (Debie et al., 2024).

A selection of issues that could be addressed through implementation research includes:

AI solutions for the health workforce
Reduce the gaps in required skills and training through customized curricula.
Explore ways to strengthen workforce diversity to address the population's needs with tools and through people who can deliver respectful and quality care.
Develop and test tools that strengthen positive and empathetic relationships between providers and patients.
Develop AI-enabled solutions for workforce planning, especially in the context of addressing surge capacity.
Support the health workforce in managing the rising trends in self-care.

Community: One Health surveillance and solutions

As interactions between humans, animals and the environment grow in complexity, AI solutions are increasingly being considered and used to address these One Health challenges through the use of large data-driven algorithms, data modelling and a variety of sensors (Pandit & Vanak, 2020; Parums, 2023). Using AI algorithms to look across these vast datasets can serve as a useful tool for prediction by drawing on processes such as spatial modelling, risk prediction, misinformation control and disease forecasting, among others (Olawade et al., 2023).

Public health surveillance, which occurs at the global, regional and national levels, relies on credible and timely community-based processes. Although the focus is on communities, the idea is that processes and systems established at the community level will feed into district and national systems. A community-based One Health surveillance model allows communities to be active participants in safeguarding their health and the health of their environment (Merali et al., 2020). These health systems subsequently benefit from feedback loops generated at each level, further strengthening how social, technical, political and other processes are designed and implemented at the community level.

A selection of issues that could be addressed through implementation research includes:

AI solutions for community-based One Health
Identify and analyze models that effectively leverage institutional and citizen sources.
Investigate interdisciplinary integration, from framework development to communications, collaboration and data sharing.
Strengthen early warning and detection systems.
Use sensors and other types of cost-effective and real-time monitoring of animals, humans, water sources and insects.
Explore the connections between community-based surveillance and global health security.
Engage communities and step aside for local leadership within communities to ensure local ecosystems and context are represented in One Health surveillance systems.

Individual: Self-care interventions

Around the world, more than 400 million people lack access to essential health services (World Bank & WHO, 2017). This is due to a confluence of factors, including severe health workforce shortages, humanitarian crises and the complexity of disease outbreaks. According to the WHO, self-care represents "the ability of individuals, families and communities to promote health, prevent disease, maintain health and cope with illness and disability with or without the support of a health worker" (WHO, 2022).

The scope of self-care spans issues of health promotion, disease prevention, treatment, rehabilitation and palliative care (Jaarsma et al., 2020). The rise of self-care practices is occurring alongside severe healthcare worker shortages and increased use of AI-enabled solutions to provide tailored and personalized care (Raparthi et al., 2020). In this paper, self-care solutions are grouped into three non-exclusive categories: 1) personalized health care, 2) preventative health and early detection and 3) health promotion. These map loosely to the three categories in the WHO guideline on self-care: 1) self-management, 2) self-testing and 3) self-awareness.

Although self-care implies greater autonomy and self-determination by individuals, it does not exclude the role of physicians or other health workers. It often implies a balance between direct or indirect input from health workers and the implementation of preventative or curative measures by the individual. For example, a patient can be trained by a health worker to monitor a condition such as diabetes or high blood pressure at home using AI-enabled applications (Chatrati et al., 2022). Or AI-enabled solutions can be used at home for the early detection of respiratory infections using a cough monitor (Imran et al., 2020).

Using responsible AI solutions to improve self-care approaches is an area of research that has implications for the wellbeing of individuals, communities, societies and health systems. Well-designed, locally relevant and privacy-protecting responsible AI solutions can significantly improve health management and monitoring and empower individuals with personalized, proactive, person-centred and affordable care solutions.

A selection of issues that could be addressed through implementation research includes:

AI solutions for self-care
Examine how users engage with AI-enabled self-care tools.
Measure the nature, extent and sustainability of changes in behaviours resulting from self-care interventions.
Explore the cost-effectiveness of AI-based self-care in resource-limited contexts, including potential cost savings from reduced visits to health facilities and those resulting from improved screening and early detection.
Contemplate how AI-based self-care tools can seamlessly integrate with other processes and systems across all six pillars of the health system to support efforts to minimize fragmentation within health systems.
Explore how AI-enabled self-care solutions can support decision-making processes among individuals with varying levels of health literacy.
Fill evidence gaps on the long-term impacts of different AI-enabled self-care solutions on health outcomes and the overall wellbeing of individuals.
Explore how AI-enabled solutions could help individuals without internet connectivity or with very limited connectivity. This can involve using basic feature phones (basic phones),[5] or exploring the use of LLMs to generate radio content.

[5] Basic feature phones or basic phones are mobile devices that perform basic functions such as making and receiving voice calls and text messages. Unlike a smart phone, these phones have limited or no access to the Internet.

EVALUATION ▶ SCALE ▶ IMPACT

Complementing these entry points for implementation research that examines if, how, for whom and in what contexts responsible AI can contribute to achieving global health objectives, sustained attention should also be placed on use-oriented evaluation, appropriate scaling strategies and positive impacts on health outcomes and health systems.

Evaluation: Relevant and transparent

Evaluating the outcomes and impact of AI solutions in health care and across health systems is a critical step in the research continuum, and essential to inform if and how these solutions can be scaled (Coiera, 2019). There is a need for evaluation frameworks and metrics to assess and learn from various stages of AI development, deployment, integration and adoption into health systems (Reddy et al., 2021). Moreover, there is a need to establish systematic benchmarking and standards to evaluate the safety and effectiveness of AI algorithms when used for clinical or public health (Mincu & Roy, 2022). Specific areas for evaluation can include changes in health status, changes in behaviour, technical usability of the AI solution, economic evaluation, environmental evaluation, social impact, gender equality and inclusion, ethics and scalability. Specific evaluation questions and approaches would depend on the users and uses of the evaluation (Patton, 2017). The role of user-focused, rigorous, locally relevant and transparent evaluation models and metrics to assess and learn from the application of AI solutions to real-world health challenges is critical to learning from failures, missteps and proven practices.

The net impact of AI solutions can be challenging to manage if their repercussions are not carefully considered. This is not limited to coverage, efficiency or policy influence. It involves careful consideration of data governance, legislation, regulation of software and hardware, pricing structures and many other variables. Given the different variables at play, without consistent and concerted attention to measuring the extent to which an AI solution is responsible, the potential of passive adoption can lead to blind adoption and significant harms resulting from scaling AI solutions.

> *Evaluating the outcomes and impact of AI solutions in health care and across health systems is a critical step in the research continuum, and essential to inform if and how these solutions can be scaled.*

Scale: Choice and intention

Scaling responsible AI solutions offers opportunities to address different forms of vulnerabilities in the Global South, especially in light of the polycrisis. Achieving scale, scaling up and scaling out are mantras commonly used in the field of AI, sustainable development and global health. Some contend that regardless of how effective or successful small-scale initiatives are, they remain "like small pebbles thrown into a big pond" (Hartmann and Linn, 2008). However, in the age of LLMs, LMMs and generative AI, even if not deployed at scale, these small pebbles can lead to large ripples and have far-reaching implications (GPAI, 2023).

Not all AI solutions need to be scaled to be legitimate or to have an impact (GPAI, 2023). Recognizing that bigger or enhanced replication of AI solutions does not always translate into better health outcomes or stronger health systems, there are important decisions to be made when considering the question of scaling. First, should the project be scaled? This step is a choice and involves intention. Secondly, how can we move beyond scaling actions to scaling impact? Scaling impact requires an approach that weighs the benefits and drawbacks of different scaling trajectories on issues such as health equity, gender equality and inclusion, local leadership and ownership, policy and regulatory coherence, and strengthening processes and outcomes within and across health and health-related systems.

Any strategy to scale should be built on the results of locally relevant and transparent evaluation models and metrics. Based on the results, a research team can elaborate an intentional strategy, identify a trajectory for scaling and establish processes for course correction.

Impact: Stronger and more resilient health systems

Health and health-related interventions are generally provided as a set of packages that span different systems, sectors and actors rather than as freestanding activities (Mills et al., 2006). As public and individual health needs continue to span across the formal healthcare system and beyond, the need to strengthen health systems instead of fragmenting them is in the best interest of efficiency, effectiveness and sustainability.

The emergent research landscape for AI and global health aims to build strong, fair and resilient health systems by establishing a model that helps guide Global South researchers in their pursuit of solutions. Using an augmented intelligence approach, Global South-led implementation research efforts can generate rigorous, credible and timely evidence to address many root drivers and outcomes of the polycrisis upon us.

Drawing from the paper, some illustrative examples of how responsible AI solutions can strengthen health systems and improve more equitable health outcomes include:

Strengthening health systems and improving outcomes
Actively seek to fill gaps in data representation and disaggregation to minimize data health poverty, thus creating a more complete picture of progress and challenges as we measure against SDGs and other important national and regional targets.
Leverage data modelling and qualitative methods to prevent, prepare for and respond to individual and public health needs.
Predict and proactively address health workforce shortages, including managing surge capacity needs when shocks and crises impact health systems.
Apply methods and metrics to measure the extent to which AI solutions are being responsible in collecting data and responding to the unmet health needs of neglected and marginalized populations.
Support frontline health workers with appropriate training and supports to provide quality care; to access accurate, local language and context-specific materials; and share feedback and suggestions to improve the AI-enabled solution(s) they are using.
Foster secure and ethical forms of interoperability across information systems to address the realities of One Health, the cross-border spread of pathogens and information, and the need for collaboration across different sectors.
Reduce health expenditures and continuously optimize health system functions.
Combat the infodemic by detecting and rectifying misinformation and disinformation, thereby strengthening trust in public health and clinical health practices.

Responsible AI solutions can strengthen global health outcomes and health systems to address neglected populations and the neglected conditions that impact their health and wellbeing. Through better quality and ethically governed data, together with locally generated evidence, Global South researchers leading the research agenda will be well-positioned to influence policymaking, ultimately addressing some of the world's most pressing health challenges.

I-STOCK/HADYNYAH/MATIO ARANGO, PANOS/ABBIE TRAYLER-SMITH

Localized evidence is the foundation for developing responsible AI solutions to build equitable, responsive health systems.

Advancing the research landscape

The ability to improve individual and public health outcomes, reduce health inequities and strengthen health systems using responsible AI provides exciting opportunities. These opportunities come with an obligation to navigate important risks and protect human rights. As the deadline for the 2030 SDGs draws nearer and the compounded impacts of the polycrisis on people's health become more pronounced, the urgency to strike a fair balance between opportunities and risks is further heightened.

The paper makes a case for the role implementation research can play in the development and deployment of responsible AI solutions. By focusing on real-world contexts, implementation research can help avoid the trap of "solutionism" and its over-reliance on technology as a panacea for all challenges. Instead, the recommended approach in this paper addresses the root causes of health disparities and integrates the social and digital determinants of health, while still considering broader health system constraints and opportunities. Moreover, locally championed implementation research is proposed as a cornerstone to inform pathways to scale evidence-based and effective solutions that will bring positive, equitable and sustained changes to communities and health systems.

Advancing the research landscape for responsible AI in global health is a collaborative journey, requiring the collective efforts of diverse stakeholders across disciplines, geographies and sectors. This paper contributes to this journey by highlighting the critical role of implementation research in bridging the gap between the promise of AI innovation and its real-world effects on health systems. By focusing on neglected populations, overlooked health conditions, and the need for resilient health systems, the paper underscores the importance of localized, rigorous and actionable evidence, and the need for intentional pathways for scaling AI solutions. Alongside others working in this field, the aim of this paper is to build momentum toward a future where global health outcomes are achieved and health systems are strengthened by responsible AI that is safe, inclusive, rights-based and sustainable.

Annex 1: Glossary of terms

Artificial intelligence (AI)
A machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy (OECD, 2023).

AI models
Models feature input data, pattern-matching algorithms and output classification.

AI solutions
These cover the entire AI ecosystem, from software to hardware, infrastructure and user interfaces.

AI systems
AI systems extend beyond AI models to include other relevant data and information.

Augmented intelligence or hybrid intelligence
A subset of AI that frames how AI can help improve decision-making. It challenges the concept that computers are replacing humans and highlights how humans and machines can work together.

Bias
The tendency of algorithms to reflect human biases.

Deep learning (DL)
A type of machine learning that uses neural networks to learn complex patterns and representations from data.

Discriminative AI
A type of AI that learns from historical data to forecast or predict outcomes.

Generative AI
A type of AI that is trained on historical data and creates new content.

Implementation research
An integrated approach designed to bridge the gap between what is expected to happen when promising solutions are designed and what actually happens when they are implemented in real-world settings.

Large language models (LLMs)
Uses deep learning architecture to generate and process human-like text; for example, ChatGPT.

Machine learning (ML)
Uses statistical and mathematical modelling to learn patterns, which are then applied to perform or guide certain tasks and make predictions (WHO, 2021a).

Responsible AI
The practice of designing, developing and deploying AI systems that are safe, inclusive, rights-based and sustainable (IDRC).

Transformer architecture
A neural network architecture that can process sequential data such as texts, audio, videos and images as a sequence.

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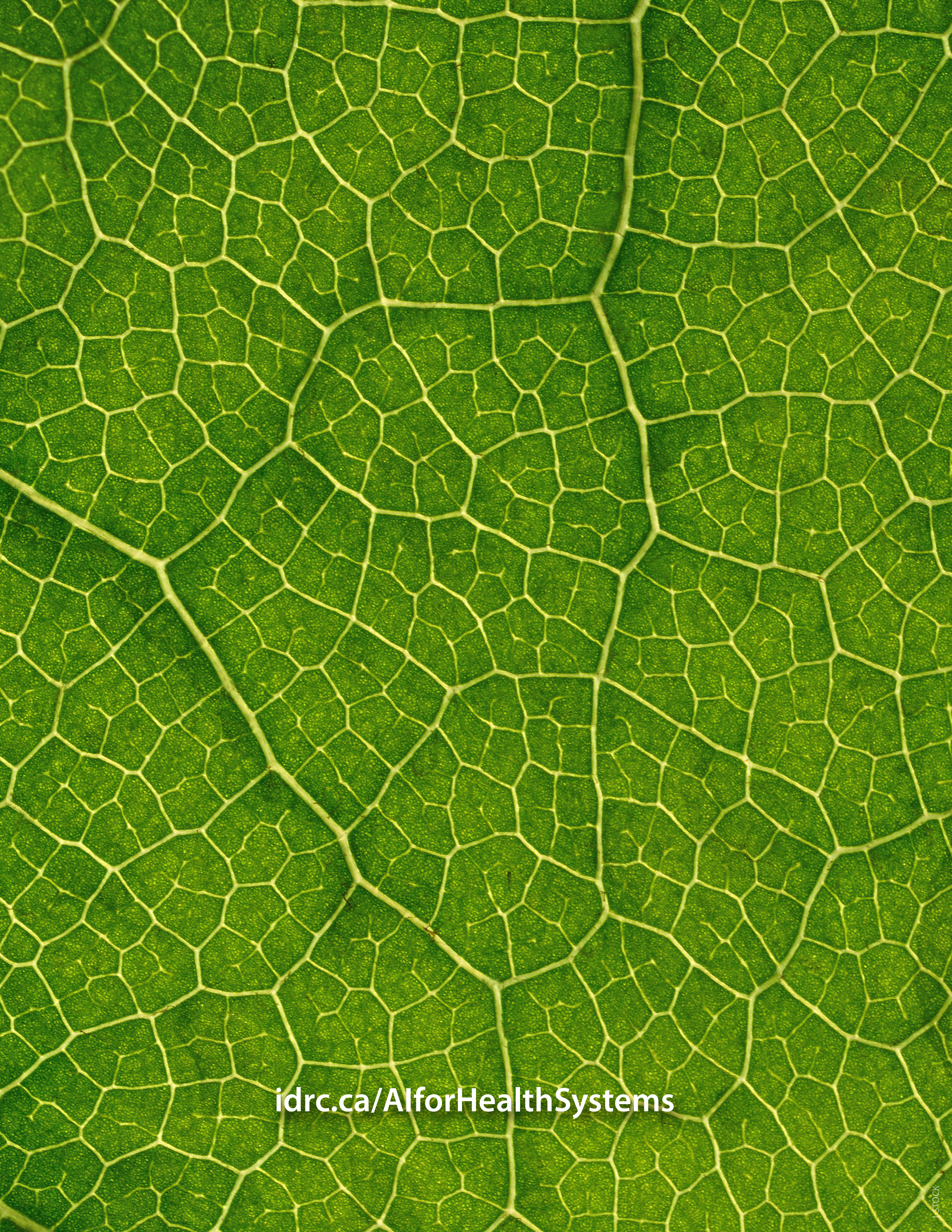
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