Artificial Intelligence in Low- and Middle-Income Countries: Innovating Global Health Radiology

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Scarce or absent radiology resources impede adoption of artificial intelligence (AI) for medical imaging by resource-poor health institutions. They face limitations in local equipment, personnel expertise, infrastructure, data-rights frameworks, and public policies. The trustworthiness of AI for medical decision making in global health and low-resource settings is hampered by insufficient data diversity, nontransparent AI algorithms, and resource-poor health institutions' limited participation in AI production and validation. RAD-AID's three-pronged integrated strategy for AI adoption in resource-poor health institutions is presented, which includes clinical radiology education, infrastructure implementation, and phased AI introduction. This strategy derives from RAD-AID's more-than-a-decade experience as a nonprofit organization developing radiology in resource-poor health institutions, both in the United States and in low- and middle-income countries. The three components synergistically provide the foundation to address health care disparities. Local radiology personnel expertise is augmented through comprehensive education. Software, hardware, and radiologic and networking infrastructure enables radiology workflows incorporating AI. These educational and infrastructure developments occur while RAD-AID delivers phased introduction, testing, and scaling of AI via global health collaborations.

Artificial intelligence (AI) pervades nearly every aspect of society. Wall Street firms use AI as technological weapons against other stock traders. Industrial giants use AI to predict consumer demand and optimize production. Technology firms use AI to predict consumer behavior and optimize marketing strategies. In medicine, radiology is one of the most touted areas of AI applicability: the so-called robot radiologist (1). Earlier lung cancer detection, automated coronary calcium scoring, and synthetic MRI based on CT are among the many radiology AI innovations in a rapidly evolving marketplace of research laboratories, tech startups, and health care enterprises. Through radiomics, AI extracts mineable high-dimensional data from clinical images, such as automating complex four-dimensional cardiovascular flow models of the heart linked to robust genomic databases (2).

In contrast, RAD-AID volunteers in Malawi cared for a mother who traveled 2 weeks on foot to bring her toddler to undergo US of an abdominal mass. In Cape Verde, RAD-AID volunteers helped a patient who needed to undergo radiography for a hip fracture that, after a road accident, had gone undiagnosed for 2 weeks. In Tanzania, our interventional radiology team drained a 3-year-old girl's abscess, obviating exploratory surgery for an abdominal "mass." From India to medically underserved areas of Washington, DC, over 20000 women have been served by RAD-AID's mobile mammography vehicles, many with advanced breast cancers related to lack of prior screening. When radiology is scarce or absent, the impact on patients is enormous (Fig 1).

Such global health radiology gaps inspired the creation of RAD-AID in 2008, a nonprofit bringing radiology to impoverished and low-resource regions of the world. We currently have 13000 volunteers in nearly 80 health institutions in 35 countries serving in programs such as a refugee camp in Jordan, a women's health unit in Peru, and a tertiary care center in Ghana. We support radiology residency programs, such as in Guyana, Nepal, Ethiopia, Liberia, Haiti, Morocco, and Tanzania. RAD-AID created a platform for radiology capacity building through which medical imaging teams deliver innovative solutions to complex problems and collaborate across subspecialties to help resource-poor health institutions seeking tailored strategies. It is this experience and our collaborative, comprehensive approach to problem solving that we bring to AI implementation in global health radiology (Fig 2).

Whereas high-income countries (HICs) question whether AI will replace human radiologists, RAD-AID questions what AI might do for locations with few or no radiologists. Could automated image interpretation enable a few radiologists to manage the workload of hundreds? Could AI bring high-precision imaging tools to rural and remote settings? Can AI be brought to resource-poor

Abbreviations

AI = artificial intelligence, HIC = high-income country, IT = information technology, LMICs = low- and middle-income countries, PACS = picture archiving and communication system

Summary

This review examines the potential roles of artificial intelligence in low- and middle-income countries for radiology and global health development.

Essentials

- Artificial intelligence (AI) introduction in low- and middle-income countries (LMICs) should proceed differently than in high-income countries (HICs). Large differences in personnel, clinical experience, disease patterns, demographics, digital infrastructure, and radiology equipment dictate the need for a global health radiology AI strategy.
- A comprehensive model for AI adoption in LMICs integrates clinical education, infrastructure deployment, and phased AI introduction.
- Data ownership ethics intersect with health inequities because data obtained from LMICs may help produce expensive AI products that preferentially benefit HICs.
- Clinical education and data-management training, in parallel with infrastructure implementation and clear data-use policies, can enable the use of AI at the individual patient and population levels.

health institutions without preselecting algorithms and instead energize an open market of AI tools?

Many HICs are rapidly incorporating AI into health care delivery, whereas most resource-poor health institutions, particularly in low- and middle-income countries (LMICs), do not have digital infrastructure in their health care systems. Approximately two-thirds of the world lack or have insufficient radiology (3) and the inequitable use of AI could further widens radiology-related health care disparities. However, this large gap also suggests an extraordinary opportunity for AI, if successfully implemented, to impact worldwide radiology service delivery and reduce disparities.

Predictions of AI's impact on HICs are based on the premise that abundant imaging equipment and large labor forces of skilled radiology personnel can leverage new AI capabilities (4). AI in radiology may include diagnostic image interpretation, prioritized triage of worklists by acuity and abnormality, quality control, safety monitoring, expedited reporting of results to clinicians, and population health data analytics. The complexity inflicted by inadequate or absent radiology in resource-poor health institutions makes the path to AI adoption in LMICs different from that of HICs. LMICs have unique institutional and community-based considerations arising from local resource constraints, cultural skepticism, public policy, and medical practice patterns.

In this article, we address the key factors that may influence AI adoption in global health radiology outreach, and we describe RAD-AID's three-pronged strategy (Fig 2): *(a)* clinical radiology education, *(b)* infrastructure implementation, and *(c)* phased AI introduction. This integrated three-part strategy is based on data and observations from RAD-AID's decades-long work in radiology capacity building in over 30 LMICs and multiple pilot deployments of AI and informatics platforms.

Clinical Radiology Education for AI Adoption in Global Health

The first key element for AI adoption in LMICs is clinical radiology education, which includes training of radiologists, technologists, radiologic nurses, informaticists, and principal stakeholders. This collaborative training includes radiologic image interpretation, image-guided procedures, protocols, patient-workflow management, and patient safety. This training establishes the foundation for AI implementation. RAD-AID uses a site-specific tailored approach to education that integrates onsite and hands-on education with web-based didactics. Supplemental learning material is also made available from RAD-AID's partnered organizations such as the American College of Radiology, the American Society of Radiologic Technologists, the Association of Radiology Nursing and Imaging, and the Society of Interventional Radiology, among others.

In HICs, skilled radiologists can interpret AI outputs and decide whether to follow AI-based recommendations and assessments on the basis of expertise and the clinical scenario. In LMICs, such expertise and labor may be lacking. For example, Tanzania, a country of 58 million people, has only 60 radiologists, an approximate 50-fold deficit relative to the per-capita US radiologist population (5). There are fewer than three fellowship-trained breast radiologists in Kenya, where an estimated 4–5 million women need annual mammography. A robust collaborative clinical education exchange can help establish a foundation on which to build AI capabilities.

The trustworthiness of AI is a critical bottleneck in AI's adoption. The "black-box" phenomenon is a criticism of most current AI, because it lacks transparency, generalizability, and explanation of outputs. Critics seek pathophysiologic justifications for AI results (6–8). Clinical education for radiologists and technologists in LMICs can reinforce the skills necessary for critically appraising AI outputs and investigating AI's clinical utility, performance, and result justifications (8). AI simply inserted into the workflows of LMIC's resource-poor health institutions would not work without radiologists who are educated to interpret AI outputs and to apply them clinically when appropriate. Alternatively, implementing AI without education could result in blindly following the output without critical appraisal. Therefore, a strategy that integrates AI with conventional radiology education would improve radiology practice and empower local radiologists to use AI safely.

Successful AI adoption in LMICs also requires education of local radiology leadership in AI validation. A well-known problem in AI deployment is algorithm generalizability. AI usually performs significantly better when tested on data derived from the same source as the training set. At present, most data for current AI development is sourced from HICs, with some contributions from high-resource institutions in middle-income countries (9). This imbalanced data sourcing limits AI generalizability because of different demographic characteristics, diseases, and equipment. The American College of Radiology Data Science Institute has identified this data-diversity problem, which introduces ethnic, sex, and social bias, and limits health equity (10).

Figure 1: Photograph of medical imaging clinic in resource-poor rural outreach context. This is a midwifery and obstetric clinical service that uses point-of-care US for maternal and infant health program in Juana Vicente, Dominican Republic. US probe (left) is connected to a laptop computer, powered by an external battery (orange cord) because of absent electricity. The clinic was a temporary facility in a barn or shed (dirt floor and wood walls around the blue examination table) to provide urgent evaluations to pregnant women. Artificial intelligence–supported US software for skilled birth attendants could assist on-site image interpretation, gestational measurements, image sharing, and rapid obstetric triage and referral. Used with permission from Diana Dowdy, RAD-AID International.

An independent external validation of AI algorithms at different independent institutions on varied demographic groups is warranted (11,12). Global health specialists advocate that local stakeholders in LMICs administer these AI validation processes with support from global health organizations (13). This approach not only helps validate the accuracy of AI outputs, but also helps LMICs' practicing radiologists identify bias from insufficient data diversity. Such validation would require local radiologists to manage these processes with full comprehension of the clinical imaging variables, validation, outlier identification, diversity measures, and bias.

The scarcity of skilled technologists in LMICs also has a profound impact on the feasibility of AI deployments in LMICs. Thus, a comprehensive clinical radiology education program must also focus on technologists. AI targeted for assisting technologists in quality control activities can only succeed if technologists have good imaging skills. For example, Tanzania has one technologist per 115 000 persons versus the United States per-capita technologist population of one technologist per 1518 persons, a near 75-fold deficit (5). Efforts to direct AI at such a limited population of technologists leads to a bottleneck: Who will be sufficiently trained to interpret the outputs of AI when producing the images before finalizing the examination? Moreover, if the images are not produced at a minimum threshold of diagnostic quality, AI algorithms may not accurately perform analytics. Therefore, the technologist community is an invaluable constituency in global AI initiatives.

Because comprehensive clinical radiology education provides a foundational layer for AI introduction, RAD-AID began integrating AI education into conventional radiology training at LMIC sites. For example, in 2017, RAD-AID started a new radiology residency in Guyana, a country of 750 000 people where there was no previous in-country radiology training program. In 2019, RAD-AID introduced AI education so that residents could learn to label images for AI algorithm training (in collaboration with MD.ai) and use AI decision support for breast imaging (in collaboration with Koios Medical [New York, NY]). These initiatives included conventional best-practice image interpretation and methods of comparing AI outputs to human diagnostic interpretations and ground-truth data.

Similarly, in rural Peru, RAD-AID collaborates with CerviCusco, a local nonprofit clinic, on women's health outreach in the Andes mountains. RAD-AID introduced AI breast US decision support (Koios Medical) at CerviCusco to teach local imaging professionals and observe how AI outputs could be appraised for breast cancer biopsy decisions in medically underserved areas (Fig 3). These efforts are scaling up as more AI laboratories and vendors have contributed samples of algorithms to RAD-AID's educational programs as part of a vendor-neutral effort to teach AI within RAD-AID's practice-based training.

Infrastructure Implementation for AI Adoption in Global Health

Availability, accessibility, and sustainability of infrastructure are vital for AI in resource-poor health institutions as detailed in the AI global health literature (13,14). Specifically, for AI in radiology, infrastructure includes medical imaging hardware, servers, information technology (IT) networking, fast internet service, picture archiving and communication systems (PACS), electronic medical records, radiology information systems, and cloud services. The International Atomic Energy Agency reported that CT has an accessibility concentration of one scanner per 25 000 persons in HICs versus one CT scanner per 1.7 million persons in low-income nations (Fig 4), a disparity factor of over 65-fold (15). Such disparities will limit the impact of U.S. Food and Drug Administration–approved AI algorithms for CT. For example, multiple algorithms offer automated interpretation of intracranial bleeds in acute head CT imaging; however, such algorithms have limited applicability in LMICs with few operating CT scanners.

The absence or insufficiency of IT infrastructure (ie, broadband, cloud, servers, local area networks, and Wi-Fi) in most LMICs represents a significant challenge in AI implementation. Because AI clinical implementation is still in its earliest stages, different pipeline strategies are offered by research laboratories and AI vendors. Some AI is deployed in hardware such as embedded within the CT scanner, US unit, or mammography station. Other AI is deployed by using PACS as the delivery platform. Other software applications (eg, radiology information systems

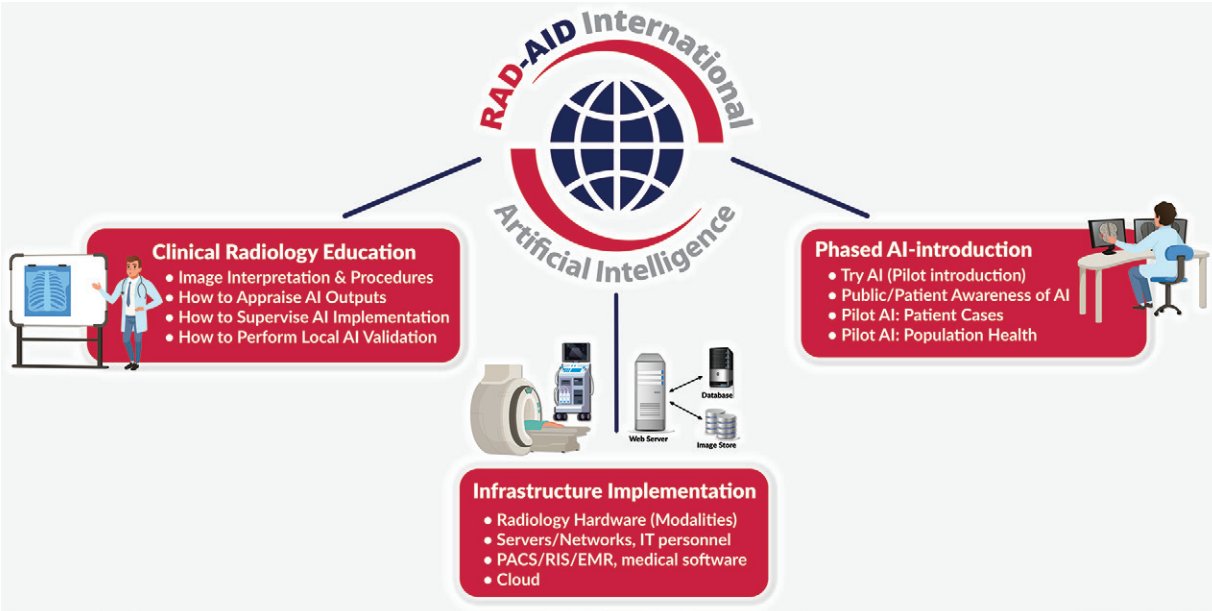

Figure 2: Schematic shows how artificial intelligence (AI) is used in global health model to integrate clinical radiology education, infrastructure implementation, and phased introduction of AI for clinical and population health contexts. EMR = electronic medical records, IT = information technology, PACS = picture archiving and communication system, RIS = radiology information system.

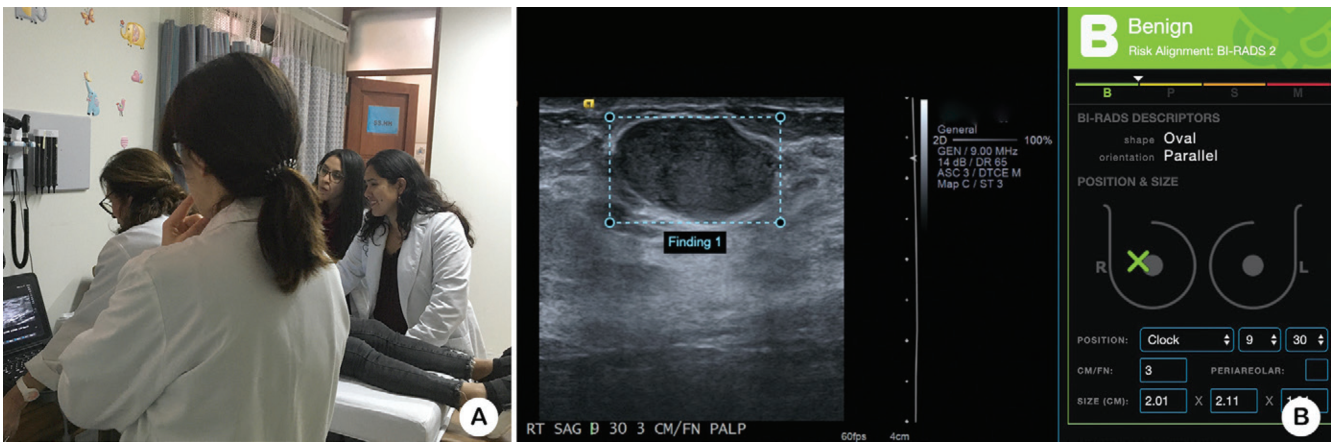

Figure 3: RAD-AID pilots artificial intelligence (AI) for breast US in the Andes Mountains of Peru for earlier detection and risk stratification of breast masses. *A,* RAD-AID volunteers and local Peruvian CerviCusco clinicians evaluate a symptomatic patient with a breast mass by using US. After US, the operator drags a box-shaped region of interest over the mass on the image and directs the AI algorithm to analyze the mass. Photo Source: RAD-AID Peru, with permission from CerviCusco. *B,* Sample output from the AI algorithm of a breast mass on a US image. The AI algorithm risk stratifies the mass as benign, corresponding to a less than 2% risk of malignancy, equivalent to a Breast Imaging and Data System (BI-RADS) 2 assessment category. Used, with permission, from Koios Medical.

and electronic medical records) operate AI on the basis of data from the modalities. There is also AI that can run via the web independently of the PACS, hospital software, and hardware. Although the exact IT of AI varies, all these options require that the hospital have basic infrastructure to support image production and radiologic image transfers. If such data management infrastructure is insufficient, how is AI to be installed and updated? PACS, for example, is widely absent in LMICs. Its absence hampers delivery and maintenance of AI.

Data management regulation is also part of the necessary foundation for AI implementation. These regulations interface with legal and ethical paradigms for how data should be stored, anonymized, accessed, transferred, and processed. In addition to lacking imaging devices and IT infrastructure, many LMICs have not yet adopted comprehensive and consistent regulatory systems for health data management (14,16). A clear regulatory framework is vital because legal uncertainty can delay technological investment.

RAD-AID's work in building radiology infrastructure in LMICs is synergistic with building capacity for AI implementation. One example of infrastructure expansion in resource-poor health institutions is the RAD-AID Friendship PACS program (Fig 5), which includes a donated on-site server, web-enabled PACS software, and cloud infrastructure as a platform that can deliver and run AI applications (17,18). The servers in RAD-AID Friendship are specially configured to be compact and

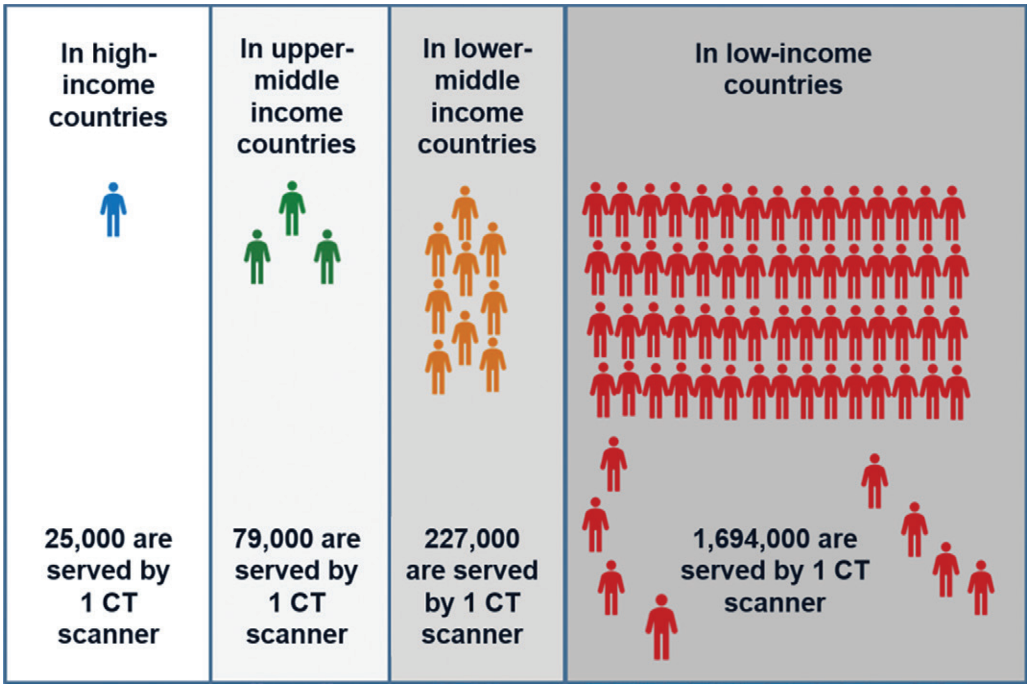

Figure 4: Comparison of CT accessibility in low-, middle-, and high-income countries. Used, with permission, from International Atomic Energy Agency.

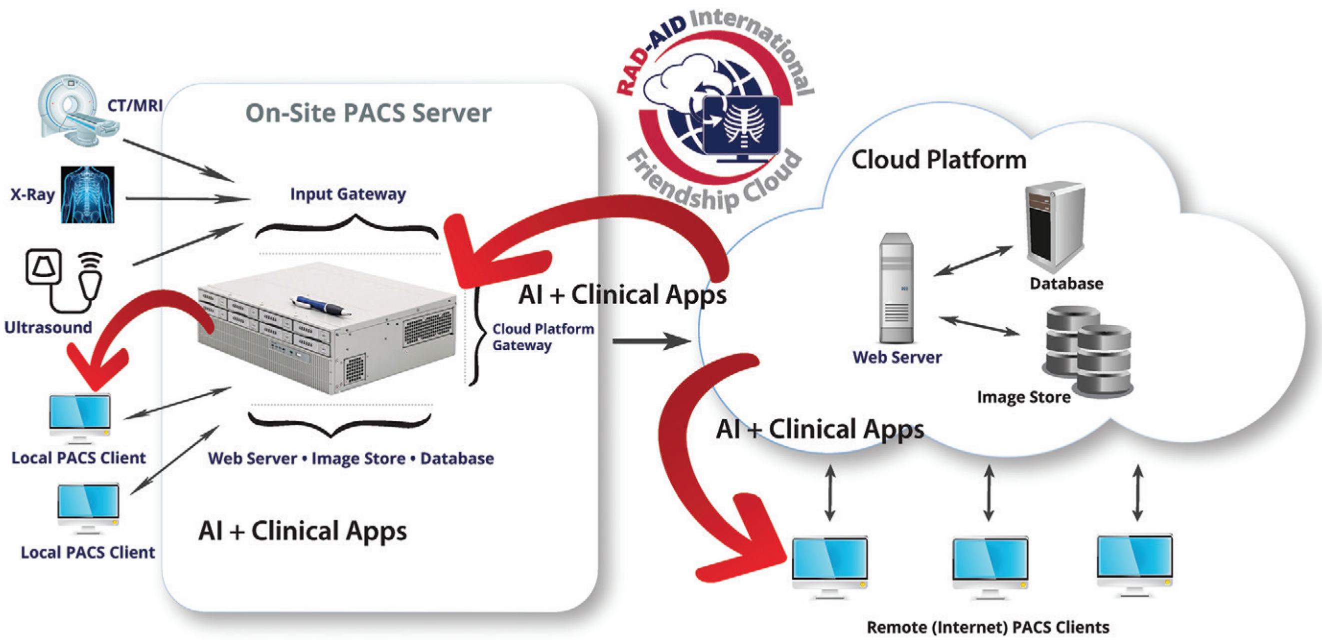

Figure 5: Diagram of RAD-AID Friendship system illustrating data management and software applications. Data flows (thin black arrows) among radiology modalities, servers, cloud, and local or remote clients. Artificial Intelligence (AI) for radiology applications (red arrows) are deployed, updated, and operated for delivering clinical decision-support outputs. PACS = picture archiving and communication system.

temperature resistant so that resource-poor health institutions do not need to construct expensive climate-controlled server rooms. The PACS software is preinstalled on the portable server to decrease demands on limited on-site IT personnel, and the cloud architecture is preconfigured to provide cost-effective scalable storage, backup, and remote access. The on-site PACS provides users at the local institution ready access to data, and cloud backup can be scheduled to run during off-peak hours when bandwidth usage is low. In 2018–2020, RAD-AID Friendship systems (in collaboration with Ambra Health and Google Cloud) were installed at University College Hospital in Ibadan, Nigeria; Lao Friends Hospital for Children in Luang Prabang, Laos; and two hospitals in Guyana (Bartica and Georgetown Public Hospitals).

Other RAD-AID IT infrastructure contributions included the following: MiniPACs (local storage without cloud connectivity) donation implementations in Nicaragua, Nepal, and Guatemala; enterprise PACS/radiology information system in Korle Bu Teaching Hospital in Ghana (in collaboration with IBM Watson Health Imaging); and enterprise PACS at Ethiopia's Black Lion Hospital (in collaboration with MedWeb) (19). These radiology infrastructure initiatives combined with RAD-AID's on-site technical, clinical, and informatics education teams provide an essential foundation for future AI delivery. For example, RAD-AID instituted workshops to train in-country radiology IT personnel in Ghana (in 2018), Tanzania (in 2019), and Guyana (in 2020), with ongoing educational training partnerships between RAD-AID and the Society for Imaging Informatics in Medicine. This training of in-country IT personnel is critical for sustainable radiology infrastructure and AI utilization.

RAD-AID integrated these IT infrastructure buildouts with radiology hardware deployments to increase accessibility of imaging modalities. For example, RAD-AID collaborated with the Philips Foundation to implement and support CT scanners in rural Guyana at New Amsterdam and Bartica Hospitals (20,21). RAD-AID is similarly supporting CT installations and CT education in Cameroon in collaboration with French-speaking African nations' Ministries of Health and Siemens Healthineers. RAD-AID Nursing provides safety training for new adopters of CT and interventional radiology modalities. In collaboration with Bayer, RAD-AID introduced an intravenous-contrast training and safety program for CT and MRI (22).

Similarly, RAD-AID has contributed US units to institutions by using diagnostic and point-of-care US in parallel with RAD-AID's on-site US training programs. This occurred in Tanzania, Grenada, Haiti, Jamaica, Peru, Nepal, Laos, Malawi, and Liberia (23,24). These examples show that infrastructure deployments can synergistically complement educational efforts so that skills and equipment advance in tandem.

RAD-AID's infrastructure support has also enabled mobile outreach to marginalized populations who cannot engage radiology facilities. As examples, RAD-AID has supported mobile radiology outreach through local partners in India (Asha Jyoti Mobile Women's Health in collaboration with Philips Foundation); Appalachia (Health Wagon in Virginia, in collaboration with Philips Foundation); and a Washington, DC mobile mammography program (Breast Care for Washington in collaboration with Hologic) (25,26). These infrastructure contributions and buildouts not only increase access to conventional radiology services, but also provide the essential foundations for AI adoption. Unless AI is delivered by using a strategy that bypasses PACS, the absence of PACS across LMICs can impede arrival of AI. Without cloud connectivity, data storage, and data management frameworks, resource-poor health institutions also cannot effectively engage AI. Thus, infrastructure implementation and support are necessary steps if AI is to find fertile ground for adoption.

Phased AI Introduction for AI Adoption in Global Health

The third component of RAD-AID's AI strategy incorporates the phased introduction of AI synchronized with clinical education and infrastructure implementation. AI is incrementally rolled out in LMIC radiology enterprises along with attention to data privacy rules, ethics, and best-practice methods at the individual patient and population health levels. An important ethical consideration is the allocation of scarce medical resources. A phased AI introduction encourages appropriate and sustainable allocation of resources to AI without neglecting other more urgent health care needs, for example, infection control. This phased AI introduction also includes public education to encourage patient acceptance and creation of well-defined public policies regarding AI utilization. This model aims for resource-poor health institutions to gain experience with AI at the introductory phase. It augments stakeholder participation in AI and fosters support from local medical professionals, patients, and broad segments of the health care sector. This is important because evidence indicates that patients trust AI more if assured that radiologists will supervise outputs for clinical decisions and if data are confidentially managed (27,28).

AI introduction is an opportunity for resource-poor health institutions to try out different algorithms on a variety of platforms (eg, imaging modality, PACS, cloud, and hardware) across different clinical contexts (eg, breast imaging, CT, MRI, interventional, and US) to assess AI accuracy and ease of use. To execute this strategy, RAD-AID received donated software from multiple vendors to create a vendor-neutral educational forum, in which RAD-AID presents AI workshops and case-based education for LMIC hospital partners to try out software algorithms. These workshops are integrated with the other education and infrastructure deployments already described in this article, to incorporate AI education into radiology capacity building. This strategy has the added benefit for AI developers to receive constructive feedback.

Another important part of this AI introduction in our proposed model is full attention to legal, regulatory, and ethical aspects of AI implementation, particularly in safeguarding protected health information, data privacy, and security. These frameworks significantly influence how data should be stored, anonymized, accessed, transferred, and processed. Frameworks for data rights are still developing in LMICs, with considerable variance across countries and jurisdictions (7,14). Some countries have stipulations about the use of cloud storage on the basis of the locations of the cloud within or outside national borders, what types of data are transmitted, and whether data are deidentified. The introductory phase of AI engagement proposed in our model, therefore, prioritizes collaboratively analyzing applicable legal guidelines.

For many institutions, piloting AI clinically also requires institutional permissions, particularly if software is to be installed on-site or if the software and/or data involve cloud transmissions. If the software is U.S. Food and Drug Administration and/or CE marked (European Economic Area) or has received other national government-derived safety clearance, the use of AI in the institution will proceed with those active regulations for patient care. If the software is investigational or has research dynamics intended for hypothesis testing and publication, it is important for the radiology department to determine whether institutional review board approval is necessary.

The ethics of data ownership are also now intersecting with those of health equity. A recent report from the United Nations Conference on Trade and Development warned that LMICs are "becoming providers of raw data while having to pay for the digital intelligence produced" (29). Data harvested from poor countries may help production of expensive products from high-income countries that poor countries must then pay more to obtain, just as historical trade in raw materials and commodities for high-end manufactured goods created similar dependencies (ie, mercantilism or neocolonialism). The lack of clear legal and regulatory frameworks for data rights exacerbates this risk of economic imbalance in AI. This ethical challenge intersects with the health equity problem: Without sharing and exchange of data, AI may not be created for LMIC populations. Therefore, data sharing is an important part of making health equity possible.

To further address these critical issues, our model includes RAD-AID's development of the RAD-AID Friendship Data Trust, which offers resource-poor health institutions the opportunity to contribute anonymized data to a not-for-profit collective data trust to engage AI developers willing to make AI software available pro bono to the hospital. This increases collective leverage of LMICs on data ownership and procures greater access to AI while also empowering AI innovation. This strategy is also designed to stimulate locally and globally driven AI development.

The RAD-AID Friendship Data Trust requires synergistic clinical education, infrastructure expansion, and AI introduction described throughout this article. Along with data rights and fair data-sharing provisions for AI, resource-poor health institutions need the skills and resources to properly manage radiology data for AI development. Because AI filters training data to improve outputs, fostering collaborations between resource-poor health institutions and AI developers can raise the quality of AI and accelerate adoption.

With implementation of AI, utilization can clinically impact LMICs at both individual patient and broader population levels. This involves piloting AI in interpretation and processing of individual radiology examinations, such as mammograms, CT, MRI, and US examinations. For populations, groups of cases with similar findings, related causes, diseases, and features can be analyzed for epidemiologic trends. Some examples include the number of cases of tuberculosis that are detected in the institution or community, or the number of mammograms on which there are lesions suspicious for cancer needing workup, or the number of US examinations that suggest fetal anomalies. These analytics can produce calculations of incidence, prevalence, and other epidemiologic metrics to inform public health research and policy.

At the population level, such pilot programs may be helpful in detecting infectious disease outbreaks. In the recent outbreak of coronavirus disease 2019, CT findings were found to be helpful in characterizing the infection, which has been true in other respiratory infection outbreaks such as H1N1 influenza, Middle East respiratory syndrome, and severe acute respiratory syndrome (30–32). Radiology AI could play a significant role in detection of infectious disease outbreaks if we deploy AI in resource-poor health institutions.

Conclusion

Artificial intelligence (AI) can bring extraordinary benefits to resource-poor health institutions but requires thoughtful collaborative implementation. The introduction of AI into low- and middle-income countries (LMICs) will proceed differently than in high-income countries because of stark differences in personnel, clinical experience, disease patterns, demographics, and radiology equipment. Resource-poor health institutions need a more holistic approach for simultaneously integrating clinical radiology education, infrastructure implementation, and phased AI introduction. Our model prioritizes well-rounded strengthening of radiology capabilities so that AI can be used and developed collaboratively in LMICs.

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