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Bridging the AI Gap in Clinical Imaging: Opportunities and Strategies for Low- and Middle-Income Countries

Yonathan Gebrewold Soreta[1]*, Afom Tesfalem Andom[1], Melino Ndayizigiye[1], Chase Yarbrough[1,2]

1. Partners In Health Lesotho, Maseru, Lesotho
2. Division of Global Health Equity, Brigham and Women's Hospital, Boston, MA, USA

* **Corresponding author.** Contact: ygebrewold@pih.org

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Abstract

Rapid advancements in artificial intelligence (AI) are transforming healthcare delivery. However, the adoption of AI in healthcare delivery and radiology service in low- and-middle-income countries (LMICs) lags behind advances in high-income countries (HICs). As a result, LMICs are not yet reaping the benefits of AI witnessed in the rest of the world. This disparity in utilization of AI is likely to lead to further widening of the existing gaps between these regions in economic prosperity and health. Our article describes the existing opportunities and rationale for investing in AI adoption in LMICs. It also highlights the potential benefits of AI in healthcare and medical imaging in the context of emerging and developing countries. Finally, a path forward for equitable AI development and usage is presented.

Introduction

The world is in the midst of a technological revolution. Artificial intelligence (AI) is transforming our lives at an unprecedented pace. Even though AI is now infiltrating every sector of the global economy, its impact is arguably most pronounced in healthcare. In particular, the medical imaging segment has attracted considerable interest from AI developers and industry leaders in recent years. This phenomenon is reflected in the remarkable growth over the past few years of AI-related publications, applications to regulatory bodies for approval of diagnostic AI tools, and the increasing adoption of AI tools in radiology work-flows (1-4).

Beyond lesion detection, classification, and segmentation, innovative AI solutions are being deployed to enhance radiology workflows, from image acquisition to reporting. Deep-learning reconstruction models are effectively implemented for CT and MRI image optimization and reconstruction, reducing scan time for patients without compromising image quality (5-9). AI-powered protocol recommendation tools have improved and standardized cross-sectional image acquisition, resulting in better image quality (10-11). The generation of synthetic CT images from MRI scans using generative AI models has shown promising results in reducing radiation burden for patients (12-13). Similarly, generative adversarial networks (GAN) for the purpose of synthetic contrast-enhanced image generation from non-contrast studies have presented a viable alternative for patients with contraindication for iodinated contrast medium (14-16). Recurrent neural networks (RNNs) and, more recently, transformer architectures, which form

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the backbone of large language models (LLMs), are being utilized for report classification tasks, to extract structured data from narrative radiology reports, generate impressions from the body of radiology reports and provide lay summary for patients (17-18).

Although not as established as in HICs, adoption and integration of AI into healthcare and radiology services in LMICs has shown promising results in addressing challenges in healthcare such as shortages of radiologists. However, these regions are underprepared for comprehensive expansion of AI (19). Beyond just importing commercially available AI tools, countries in this part of the world should be enabled to leverage their potential by curating medical imaging data, and training and deploying AI models that meet their local needs.

The "why": Opportunities and rationale for investment in AI in LMICs

Expansion of radiology services and the shift to digital systems

The expansion of AI in clinical radiology is closely linked to growth in digital imaging services. Availability of radiographic equipment, information systems and robust IT infrastructure are the minimum essential for AI implementation. Even though the ratio of imaging equipment to population is still very low in LMICs, these regions have seen significant growth in investment on imaging equipment in recent years. In addition to installation of new diagnostic imaging machines, conversion of analogue systems to digital has also seen significant growth in these countries (20). The expansion and digitization of radiology services could lead to the generation of increasingly large volumes of medical imaging data, which — if aided with proper IT infrastructure and expertise — will offer an opportunity for advancement of AI technology in a local context. The acquisition of medical imaging data pipelines will then enable LMICs to create clinical imaging data repositories and ensure data ownership and security.

Scarcity of radiologists

A compelling rationale for adopting diagnostic AI tools in LMICs is the scarcity of radiologists, which poses a major setback in the delivery of quality healthcare services in these regions. This problem is particularly pronounced in rural settings, as radiologists tend to concentrate in major cities (21). Teleradiology services have been shown to be effective in bridging this gap in LMICs (22-23). Additionally, the integration of AI technology in teleradiology platforms has shown promising results in further improving radiology services, particularly in the fight against pulmonary tuberculosis (TB) in Africa and other developing regions. In addition to triaging symptomatic patients, CXR is currently being implemented in community-based screening programs in countries with a high burden of pulmonary TB (24). Computer assisted detection (CAD) software has emerged as a practical solution in obtaining accurate and timely interpretation of the large volume of CXR studies performed in programs where radiologists are lacking. Where radiologists are present, such tools have been found to improve radiologists' diagnostic performance and timely reporting, which further highlights the role AI could play in improving the efficiency of healthcare delivery in LMICs.

A practical example of such AI integration can be found at the authors' institution (Partners In Health Lesotho) where a CAD system called qXR, created by Qure.ai (Mumbai, India) (25), is integrated with a web-based platform called qTrack that enhances and streamlines TB diagnosis and treatment. Chest x-rays from five remote clinics in Lesotho are de-identified and uploaded onto a cloud server where they will receive a probability score for the presence of TB from the AI algorithm. The image and AI label are then reviewed by a radiologist based in the capital, Maseru. The radiologist's final report is made immediately available to the clinical caregiver at the remote clinics, as well as to consultants in the capital. This approach has enhanced the fight against TB in Lesotho, which has one of the highest TB burdens (664 cases per 100,000 people, and a remarkably low detection rate of 32-47%) (26-28). According to unpublished programmatic data from PIH-Lesotho, the TB detection rate has risen from a mere 22% to 63% within one year of the implementation of this program.

Ensuring equitable economic benefits of AI for LMICs

Another persuasive reason for investing in the expansion of medical AI in LMICs is its contribution to local economic growth. The global market share of AI in medical imaging was estimated to be over 1 billion USD in 2023. However, this figure is expected to be followed by an exponential compound annual growth rate (CAGR) of nearly 35% in the years 2024-2030. In addition to a linear increase in revenue, this massive growth has brought huge employment opportunities in HICs. It has also provided lucrative business milieu for smaller AI and tech startups to scale up their businesses through partnerships, product or service sales, and mergers and acquisitions (4). However, this phenomenon is largely true in the developed world and is nearly non-existent in LMICs. Unless governments in LMICs and their international partners carefully plan and strategically implement the groundwork for adoption of AI in healthcare and other sectors, countries in this region will continue to lose potential economic benefits from this massive industry, further widening the existing economic inequality between LMICs and wealthier nations.

Unfortunately, LMICs have a long way to go in creating the basic economic and regulatory frameworks for innovation in AI. According to the International Monetary Fund's AI Preparedness Index (AIPI) — which considers countries' digital infrastructure, human capital, labor policies, innovation, economic integration and regulation — most developing countries, particularly African nations, score far below the overall average. The AIPI also highlights how far behind these countries are in AI adoption, and the need to ”lay a strong foundation by investing in digital infrastructure and digital training for workers” (19).

Finally, a discussion about equitable distribution of AI benefits would not be complete without addressing the potential challenge of exploitative practices from AI companies, where imaging data repositories from LMICs could be utilized to develop new or improve on existing AI tools without proper engagement or meaningful advantage to the communities from which the data is drawn. Ensuring strict adherence to guidelines of good clinical practice cannot be stressed enough. Ethical principles and guidelines meant for development of new drugs and clinical trials should be applicable in development of medical AI tools (29). In this regard, AI-specific ethical guidelines, such as the European Commission’s Ethics Guidelines for Trustworthy AI could serve as a comprehensive resource to address this challenge (30).

Need for monitoring and quality control of medical AI in LMICs

A growing number of commercially available AI tools are currently being integrated into radiology workflows in developing countries. While this is beneficial in many ways, the deployment process requires careful planning, preparation and paying due consideration to the many pitfalls that could arise with AI deployment. While most of the commercially available diagnostic AI tools have been well tested and validated, it is expected that their performance will be lower than reported when exposed to new patient populations. This problem of generalizability largely arises from a lack of representativeness among training datasets. It is also well known that biases embedded in training datasets are likely to be carried over to the final AI algorithm, which negatively affects the model’s performance when deployed in a new data environment. In the case of diagnostic AI tools in particular, it is reported that algorithms are able to tell the race, body type and gender of patients from medical images across a variety of modalities regardless of anatomic regions scanned (31-32). It should then be expected that a particular AI model might use those non-clinical features to carry out disease classification or other tasks. Moreover, according to recent guidelines, ensuring nondiscriminatory performance of clinical AI tools across racial or other group identifiers is incumbent on the institution deploying those tools in clinical workflows (33).

Even where such biases are minimal, AI features that are predictive in one subset of a population for the purpose of image classification are likely to be less effective in another. These problems highlight the need for employing multi-site training datasets (‘federated’ learning), or enabling post-market automated feature engineering where AI algorithms learn to discover relevant features on their own when deployed in new settings (34).

In addition to changes in population demography, the adoption of newer machines or imaging protocols in radiology workflows inevitably leads to decline in AI performance over time. Updates made to an existing AI tool by a vendor, or introduction of a newer version, may also result in unintended poor performance outcomes (35). Very rarely, exposure of a continuously learning AI to an unusual data point may lead to ‘catastrophic forgetting’ which severely compromises the AI’s performance (34). It is therefore crucial that institutions or national programs planning to adopt commercially available AI tools be aware of these caveats and devise methods to identify and mitigate such problems. This usually involves testing and validating the performance of adopted AI algorithms in a new, well-curated and locally representative dataset during adoption, and instituting periodic or continuous AI monitoring post deployment (35). Furthermore, re-training of adopted AI tools could help customize and improve the performance of AI algorithms to match the target population where such tools are deployed (36). Inevitably, the infrastructure and other capacity-building measures meant for AI testing and monitoring are expected to lead to the creation of data pipelines, imaging data repositories and enhanced expertise which will, in the long run, create an enabling environment for research, local evidence generation and innovation in LMICs.

The "how": The way forward

For the reasons discussed above and more, it is imperative that LMIC governments and their global partners strategize and make a commitment to facilitate adoption of AI in healthcare — especially in clinical imaging — in the near future. This essentially translates to helping LMICs build robust IT infrastructure, institute health information systems, invest in human capital development, and devise regulatory frameworks.

Improving IT infrastructure is fundamental in facilitating the adoption of AI and other modern healthcare technologies in LMICs. Unfortunately, poor internet connectivity still poses a significant hurdle in the adoption of telemedicine, disrupting real-time consultations and delaying critical diagnoses (37). According to the International Telecommunication Union (ITU), one third of the global population remains offline. More importantly, the disparity in internet usage between HICs (93%) versus LMICs (54%) and urban (83%) versus rural populations (48%) is growing wider (38,39). Removing technical and infrastructural barriers cannot be overemphasized if meaningful gains are to be made in AI technology adoption in LMICs.

When it comes to building strong information systems, particularly picture archiving and communication systems (PACS), the prohibitive cost of owning and maintaining IT infrastructure, expensive subscription fees for software, frequent power cuts, and inadequate networking were major hurdles in the past (40). However, with recent advances in cloud-based IT services and the availability of reliable, open-source or affordable applications, the cost of acquiring robust, secure and sustainable PACS and other health information systems in underdeveloped setups should not be out of reach. Expanding these services not only to tertiary centers in major cities, but also to district hospitals and health centers, should be prioritized. The expansion of such information systems will then play a pivotal role in enhancing imaging data curation and the creation of local imaging data repositories for the training and deployment of AI in LMICs.

Similarly, addressing the shortage of trained human capital in the field of AI should be given due attention. An accelerated and sustainable adoption of AI in healthcare can only occur with the full engagement of clinicians and radiologists. It is evident that the full benefit of clinical AI tools is dependent upon the rate of penetration of this technology among physicians, which is in turn dependent upon behavioral and technological factors that affect the pace of adoption of such innovative solutions. Perceived usefulness, ease of use, accountability and explainability are known to strongly influence adoption of any form of technology, including AI (41-42). Foundational knowledge of the working principles behind clinical AI tools are likely to increase physicians' and radiologists' trust in the specific AI tool in question (36). It is therefore equally important to familiarize end users, including radiologists, clinicians and other healthcare providers, with not only the AI tools but also the basics of their underlying logic.

In addition, it is essential that institutions wishing to deploy AI tools are aware of the drawbacks of human-AI interaction including automation bias, deskilling and algorithmic aversion, and devise ways to mitigate these problems (35). To this end, universities and medical schools should consider incorporating concepts of imaging informatics and AI into their medical and radiology residency curricula. Faculty members should be provided with opportunities to advance their knowledge in the field of AI through subscriptions to online resources and virtual or in-person training. Fostering collaboration between universities in LMICs with their counterparts in advanced nations, arranging exchange programs for experience sharing, providing on-the-job training, and designing collaborative projects with industry leaders and other willing partners will be essential for the fast adoption of AI in these disadvantaged regions. In this regard, RAD-AID's three-pronged strategy — clinical radiology education, infrastructure implementation and phased AI introduction — could serve as a guiding framework for implementation of AI in LMICs (43).

In summary, LMICs lag far behind in the adoption of AI in healthcare, particularly in clinical imaging. If allowed to continue, this will inevitably contribute to the ever-widening disparity in health indices between these countries and the rest of the world. More than just importing AI tools, emerging and developing nations should be assisted in building their own, sustainable, customized and locally relevant AI solutions in healthcare. However, this enormous task should not be left for LMICs to shoulder alone.

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