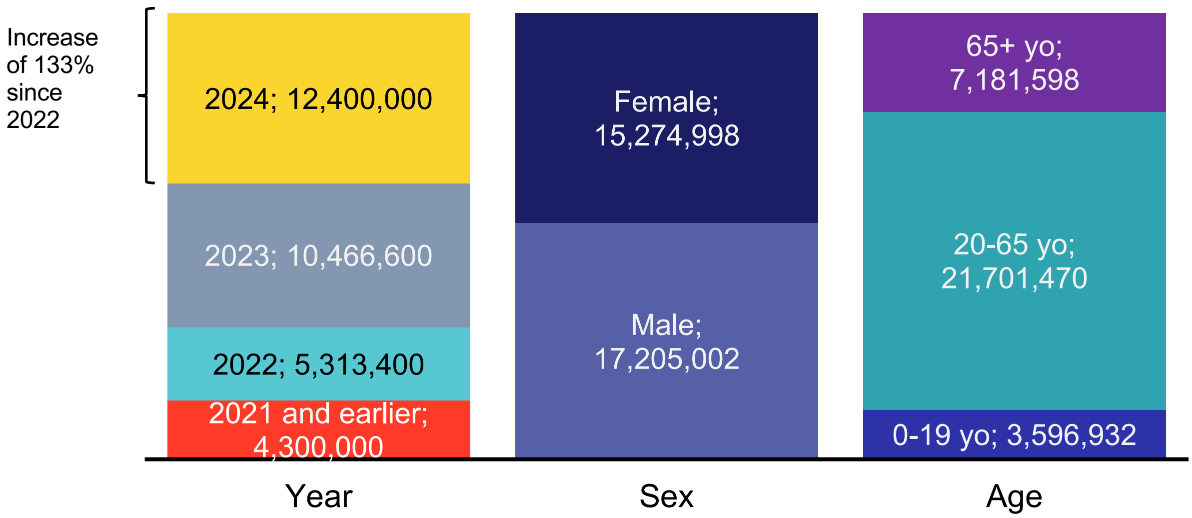
qure.ai

Creator of deep learning technology automating the interpretation of radiology exams like X-rays, CT scans, and ultrasounds, offering a chance to detect early signs of lung cancer and other diseases. Visit the qure.ai website.

I. FY2024 Impact Metrics

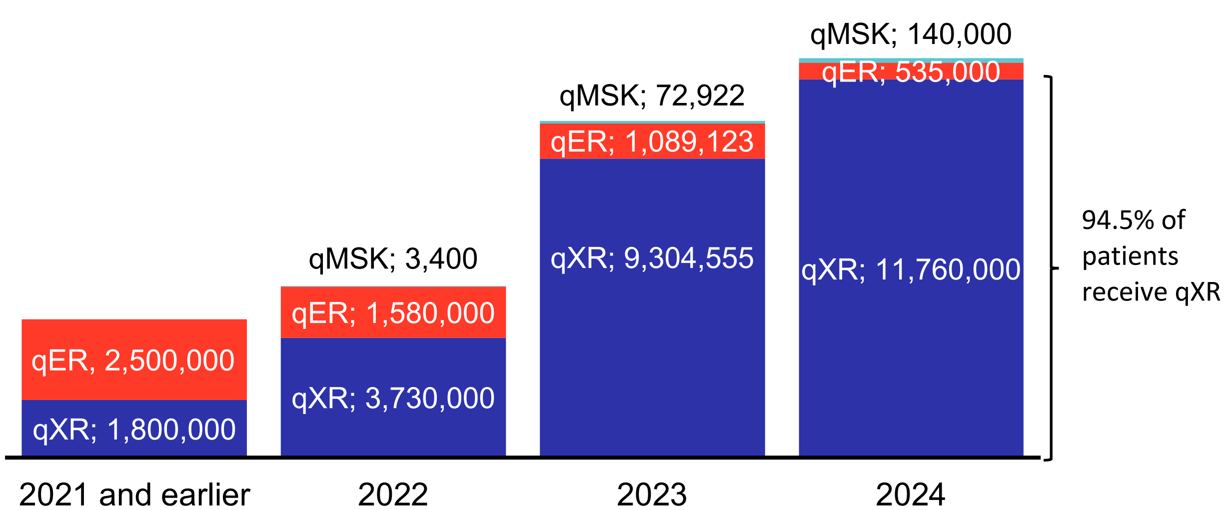
1. Number of unique patients served (cumulative)[1]

N = 12,400,000 (2024); 32,480,000 (cumulative)



2. Patients Served by Product (Annual)

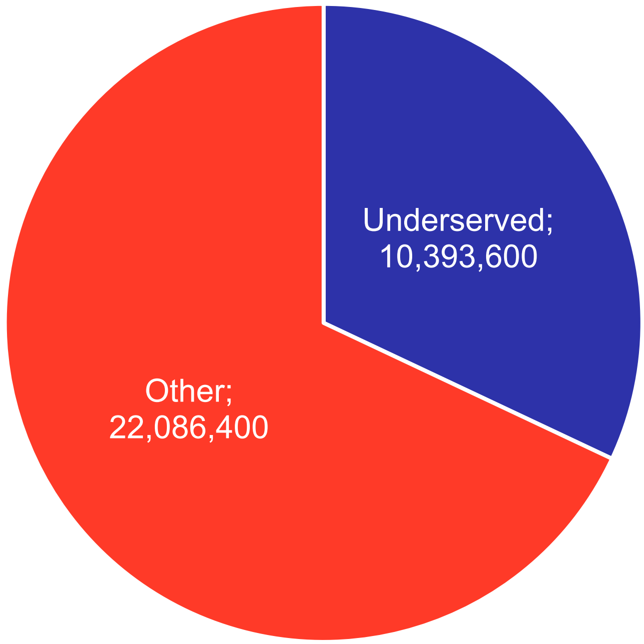
N = 12,400,000 (2024); 32,480,000 (cumulative)



[1] Test distribution by sex is 52% male:48% female

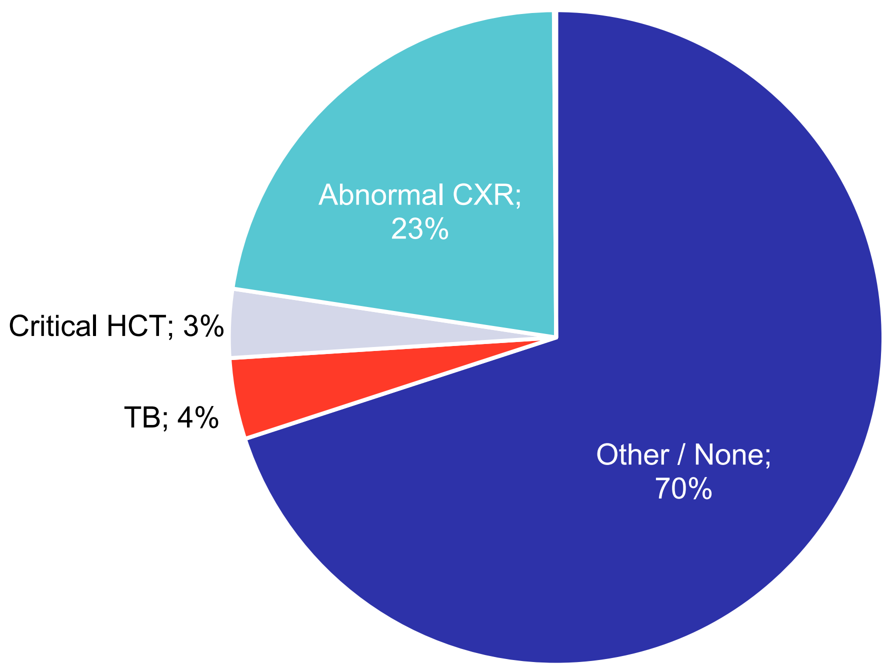
3. Total Patient Population by Underserved Status (Cumulative Estimate)

N = 32,480,000 (2024 cumulative)



4. Total Patient Population Flagged by Disease (Cumulative)[2]

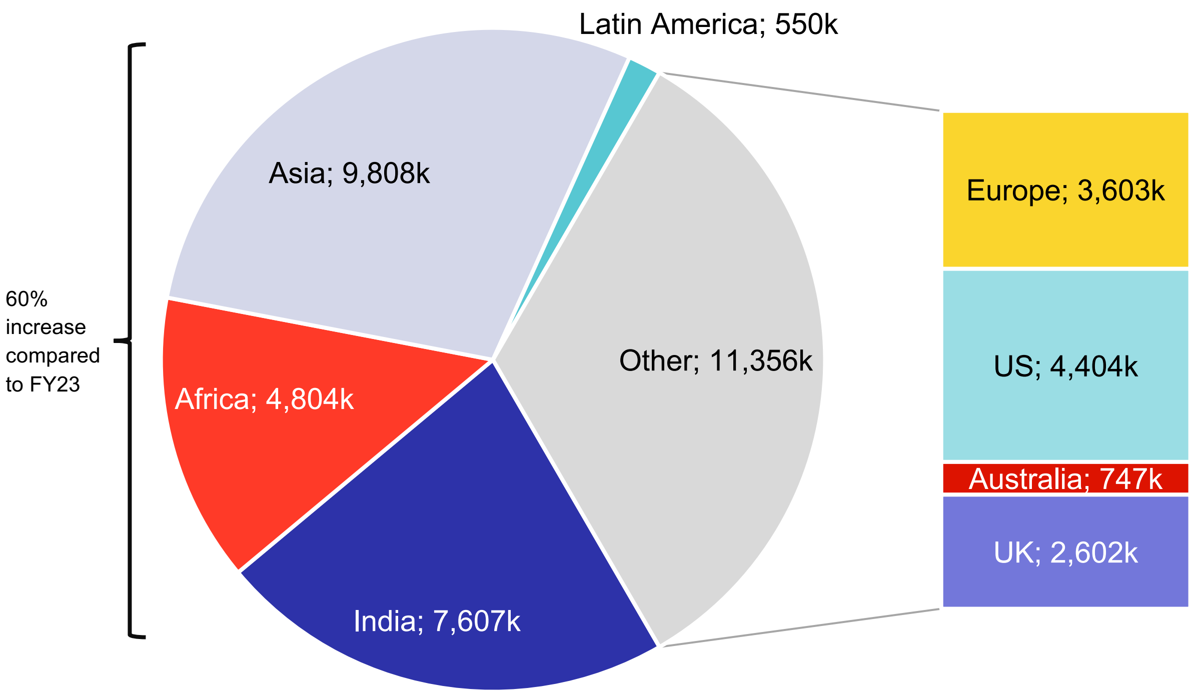
N = 32,480,000 (2024 cumulative)



[2] The Qure.ai platform flags abnormalities which are then reviewed by a clinician as part of the diagnosis process. Since a scan reviewed by Qure.ai may not show any abnormality (and would not be flagged) or return no abnormality or one outside the diseases Qure.ai focuses on, those not attributable to conditions broken out above are categorized as ‘Other /None’ for our report’s purposes).

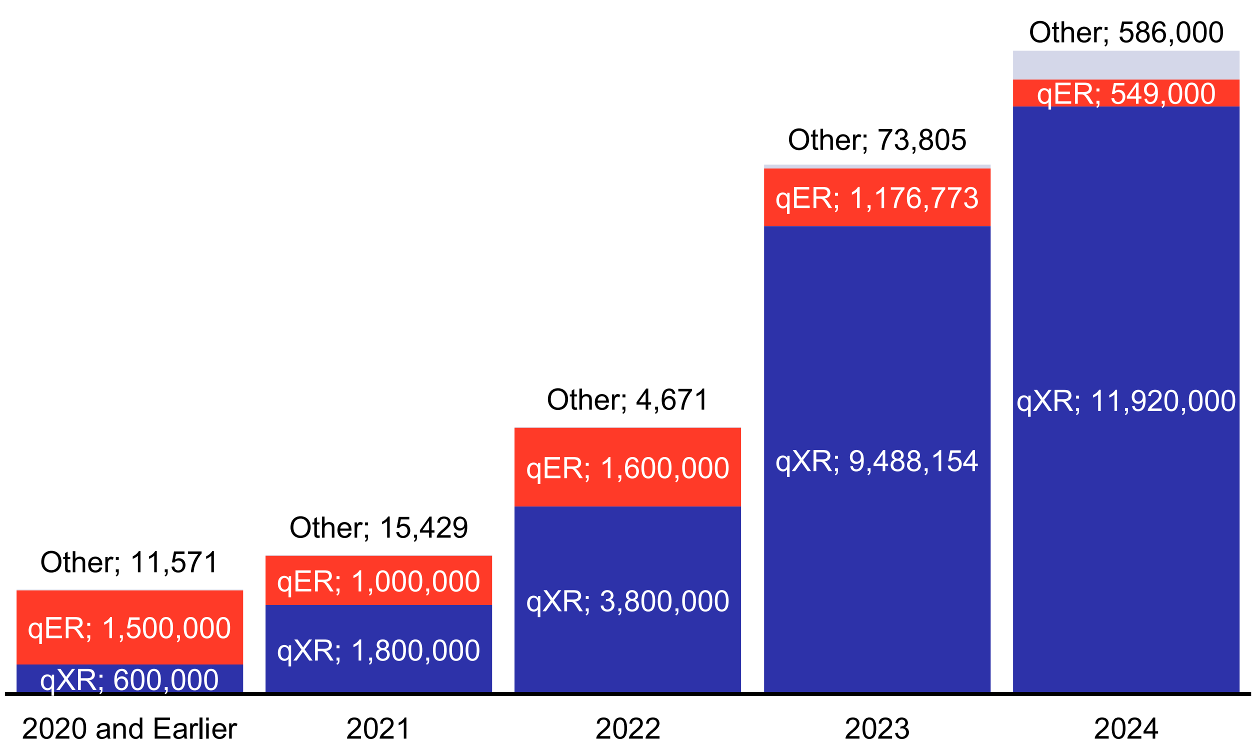
5. Total Scan Units by Geography (cumulative)

N = 34,125,403 (2024 cumulative)



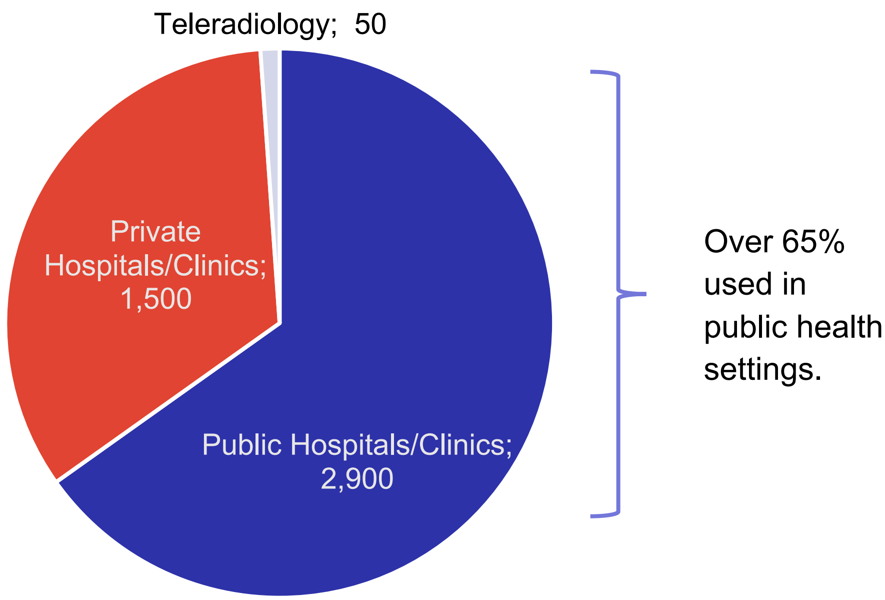
6. Total scan units by product

N = 34,125,403 (2024 cumulative)



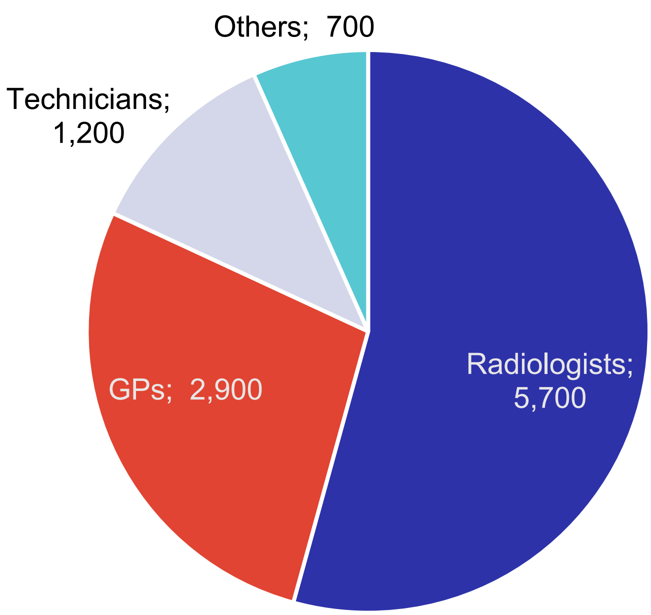
7. Facility profiles by type[3]

N = 4,450 (2024 cumulative)



8. Provider profiles by type[4]

N = 10,500 (2024 cumulative)

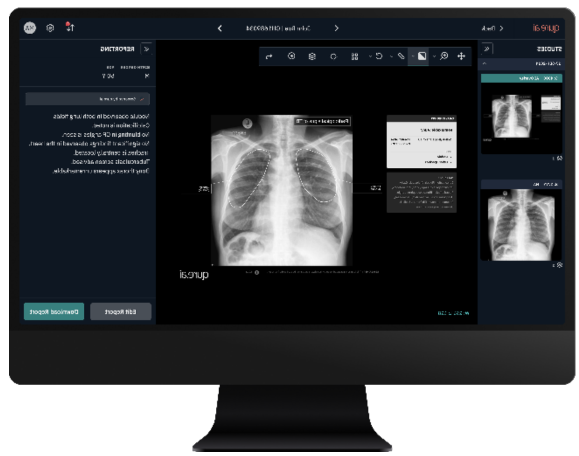


[3] A large percentage of the use cases for hospital / clinic providers (especially those in the public sector) involve scans conducted at the point of care or outside of hospitals.

[4] 'Other' providers most frequently were 1) healthcare workers working under National TB Programs, 2) state and district-level program managers, and 3) Program managers and field staff from other organizations running TB Projects for on-ground implementation.

II. IMPACT SPOTLIGHT ONE: Advancing AI-Enabled Digital Health Interventions To Help Shape and Strengthen Healthcare Systems in Low- and Middle-Income Countries ("LMICs")

A. Key Challenges in LMIC Primary Care Settings (Personnel Shortages, Workloads, and Health Data Practices), and the Use of Digital Innovations for System Strengthening



As LMICs intensify efforts to build-out their health systems in the wake of disruptive global aid curtailment, **focus** is **first and foremost** on **strengthening primary healthcare ("PHC") infrastructure**, including referral hospital infrastructure, where the majority of care services are provided.[5] While it has been understood for some time now that strengthening PHC is the **most cost-effective** approach for LMICs to

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[5] See generally, e.g., Global health 2050: the path to halving premature death by mid-century. *The Lancet.* October 14, 2024. https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(24)01439-9/abstract; Alegre, J.C., et al. Strengthening primary health care in low- and middle-income countries: furthering structural changes in the post-pandemic era. *Frontiers.* February 14, 2024. https://pmc.ncbi.nlm.nih.gov/articles/PMC10899890/; Lilford, Prof. Richard J., PhD, et al. Policy and service delivery proposals to improve primary care services in low-income and middle-income country cities. *The Lancet.* May 2025. https://www.thelancet.com/journals/langlo/article/PIIS2214-109X(24)00536-9/fulltext; Regeru, Regeru Njoroge, et al. 'Do you trust those data?'—a mixed-methods study assessing the quality of data reported by community health workers in Kenya and Malawi. *Oxford Academic.* January 16, 2020. https://academic.oup.com/heapol/article/35/3/334/5707447.

achieve broader and more sustainable patient care coverage, steep challenges to progress remain, including **personnel shortages**; **excessive workloads**; and **data collection, reporting and recordkeeping practices**, still for the most part **manually-derived**. These challenges contribute to sub-optimal clinical decision-making and related care; overstrained workforce and related performance issues; and inadequate data for informed decisions at policy/funding levels.[6]

To better understand the interrelationship between LMIC primary health data and patient care challenges on the one hand, and country-level policy/funding challenges on the other, consider the following **broad realities**:

- Primary care workers in LMICs must address a **disproportionate** share of global burdens. For example, there is an estimated **18M** people who **die prematurely** from noncommunicable diseases ("NCDs") every year, and **86%** of those premature deaths occurs in LMICs -- mostly at the PHC (and referral hospital) level.[7] Attendant data collection/reporting/ recordkeeping requirements are heavy and unremitting, yet have yielded relatively few insights about specific NCD-related burdens and risk factors, on a country-by-country basis.

- There are **not enough personnel resources** in primary care settings -- a challenge that is significant and without meaningful projected relief. With a **shortage** of **~11M** LMIC health workers expected by **2030**,[8] there needs to be more effort made to prioritize and optimize patient care, and to remove tasks that divert from this care,

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[6] See, e.g., Alegre, J.C., et al. Strengthening primary health care in low- and middle-income countries: furthering structural changes in the post-pandemic era. *Frontiers.* February 14, 2024. https://pmc.ncbi.nlm.nih.gov/articles/PMC10899890/; Gouda, Hebe N., Ph.D., et al. Burden of non-communicable diseases in SSA, 1990-2017: results from the Global Burden of Disease Study 2017. *Lancet.* Volume 7, Issue 10, PE1375-E1387, October 01, 2019. DOI: https://doi.org/10.1016/S2214-109X(19)30374-2; Lilford, Prof. Richard J., PhD, et al. Policy and service delivery proposals to improve primary care services in low-income and middle-income country cities. *The Lancet.* May 2025. https://www.thelancet.com/journals/langlo/article/PIIS2214-109X(24)00536-9/fulltext; Regeru, Regeru Njoroge, et al. 'Do you trust those data?'—a mixed-methods study assessing the quality of data reported by community health workers in Kenya and Malawi. *Oxford Academic.* January 16, 2020. https://academic.oup.com/heapol/article/35/3/334/5707447.

[7] Noncommunicable diseases. *World Health Organization.* December 23, 2024. https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases.

[8] Health Workforce*. World Health Organization*. https://www.who.int/teams/health-workforce/3#:~:text=Key%20figures,of%20the%20global%20health%20workforce; Health and care workforce -- Global strategy on human resources for health: workforce 2030. *World Health Organization.* December 20, 2024. https://apps.who.int/gb/ebwha/pdf_files/EB156/B156_15-en.pdf.

especially those tasks that lend themselves to automation and **other forms of digital assistance**.

- As described further below, PHC personnel in LMICs spend too much of their time on **manually-derived patient data collection, reporting**, and **recordkeeping**,[9] and yet the aggregated data that is generated, is often **unreliable** for broader public health use.[10] LMICs too often lack quality **population-level data** needed for meaningful disease **surveillance** and for **informed decisions** about **disease priorities** and **health budgeting** at National and sub-National levels.[11]

We bring these broad realties into further focus below, by providing a summary overview of recent literature on: (1) primary care **workforce shortages**, and related **workload burdens**, and (2) concerns presented by **manually-derived health data collection**, **recordkeeping**, and **reporting practices** -- the predominant practice still in LMICs.

1. Workforce shortages and related primary care workloads in LMICs

There is wide agreement among global health authorities around the expected significant shortage of healthcare personnel by the turn of the decade.[12] Using Sub-Saharan Africa ("SSA") as an example, the WHO projects a **6.1M** healthcare worker ("HCW") shortage in the African Region by 2030,[13] based on the needs of the population and disease prevalence.

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[9] Siyam, Amani, et al. The burden of recording and reporting health data in primary health care facilities in five low- and lower-middle income countries. *NCBI.* September 13, 2021. https://pmc.ncbi.nlm.nih.gov/articles/PMC8436492/.

[10] See, e.g., Regeru, Regeru Njoroge, et al. 'Do you trust those data?'—a mixed-methods study assessing the quality of data reported by community health workers in Kenya and Malawi. *Oxford Academic.* January 16, 2020. https://academic.oup.com/heapol/article/35/3/334/5707447;

[11] Id. Gouda, Hebe N., Ph.D., et al. Burden of non-communicable diseases in SSA, 1990-2017: results from the Global Burden of Disease Study 2017. *Lancet.* Volume 7, Issue 10, PE1375-E1387, October 01, 2019. DOI: https://doi.org/10.1016/S2214-109X(19)30374-2.

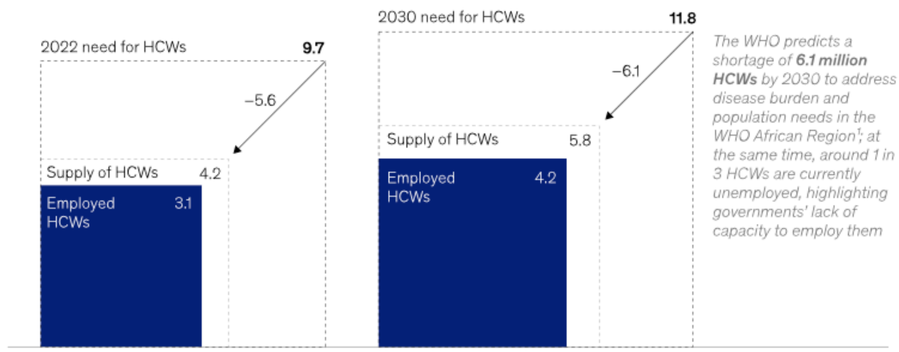
[12] Health Workforce. *World Health Organization*. https://www.who.int/teams/health-workforce/3#:~:text=Key%20figures,of%20the%20global%20health%20workforce; Health and care workforce -- Global strategy on human resources for health: workforce 2030. *World Health Organization.* December 20, 2024. https://apps.who.int/gb/ebwha/pdf_files/EB156/B156_15-en.pdf.

[13] Asamani, James Avoka, et al. Projected health workforce requirements and shortage for addressing the disease burden in the WHO Africa Region, 2022-2030: a needs-based modelling study. *NCBI.* October 22, 2024. https://pubmed.ncbi.nlm.nih.gov/39438055/. See also, Holt, Tania and Sun, Ying Sunny, et al. Overcoming sub-Saharan Africa's health workforce paradox. *McKinsey & Company.*

Exhibit 1

Sub-Saharan Africa faces a severe shortage of healthcare workers, despite widespread unemployment in the sector.

WHO African Region[1] baseline and forecasted health workforce estimates,[2]
millions of healthcare workers (HCWs)



Note: Figures may not sum, because of rounding.
[1]The WHO African Region includes all countries in sub-Saharan Africa as used in the statistics of United Nations institutions, except for Sudan and Somalia (excluded) and Algeria (included).
[2]Physicians, nurses, midwives, dentistry personnel, pharmaceutical personnel, laboratory health workers, environmental and public-health workers, community and traditional health workers, health management and support health workers, and other health workers (which include medical assistants, dieticians, nutritionists, occupational therapists, medical imaging and therapeutic-equipment technicians, optometrists, ophthalmic opticians, physiotherapists, personal-care workers, speech pathologists, and medical trainees).
Source: "Needs-based health workforce requirements to address Africa's disease burden and demographic evolution," WHO African Region, 2024

McKinsey & Company

LMICs, faced with these significant personnel shortfalls, are in the process of restructuring their primary care strategies, to create more efficient, productive care delivery, tailored to the needs and dynamics not just of their patient population, but also their healthcare workforce.[14] In 2022, Wright and colleagues[15] undertook a systematic review and meta-analysis to evaluate **burnout among PHC workers**, assessed using the Maslach Burnout Inventory Subscales of "emotional exhaustion;" "depersonalization;" and "personal accomplishments." The overall single point prevalence of burnout ranged from 2.5% to 87.9%, and the pooled prevalence (meta-analysis) was **28.1%** for "high level of emotional exhaustion;" **16.4%** for "high level of deep personalization;" and **31.9%** for "high level of reduced personal accomplishment."

November 4, 2024. https://www.mckinsey.com/industries/social-sector/our-insights/overcoming-sub-saharan-africas-health-workforce-paradox.

[14] Id.

[15] Wright, Tanya, et al. Burnout among primary health-care professionals in low- and middle-income countries: systematic review and meta-analysis. *NCBI.* April 29, 2022. https://pmc.ncbi.nlm.nih.gov/articles/PMC9178426/.

In a separate scoping review of the literature by Endalamaw and colleagues (2024)[16] involving barriers and strategies for PHC workforce developments across both LMICs and HICs, the most frequently cited barriers were issues related to healthcare delivery, such as **workloads** and financial challenges. Another notable barrier often raised in the scoping review, according to the authors, was the **shortage** of **healthcare technology** pertaining to both **information technology** and **healthcare supplies**.

AI-enabled solutions that **automate more administrative tasks**, **streamline workforce efficiencies**, and **facilitate consultative care**, including **clinical care decision-making**, will help optimize productivity, reduce burnout, and allow for greater focus on patients themselves.

2. Primary care health data burdens

a. Time burdens

Recording and reporting patient health data is the backbone of LMIC primary care **health information systems**, yet the **time requirement burdens** of creating and sustaining **manually-derived** health information systems, are substantial and a **major challenge** to care in LMICs.[17]

In 2021, Siyam and colleagues[18] sought to quantify time required for **recording and reporting** health data manually at the **PHC level** in **5 LMICs** (Cambodia, Ghana, Mozambique, Nigeria, and Tanzania). Findings from that study showed that health workers were spending an **unduly large percentage** of their care consultation time, **collecting and reporting**

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[16] Endalamaw, Aklilu, et al. Barriers and strategies for primary health care workforce development: synthesis of evidence. *NCBI.* March 27, 2024. https://pubmed.ncbi.nlm.nih.gov/38539068/.

[17] See, e.g., Regeru, Regeru Njoroge, et al. 'Do you trust those data?'—a mixed-methods study assessing the quality of data reported by community health workers in Kenya and Malawi. *Oxford Academic.* January 16, 2020. https://academic.oup.com/heapol/article/35/3/334/5707447; Basera, Tariro J., et al. Community surveillance and response to maternal and child deaths in low- and middle-income countries: A scoping review. *PLOS One.* March 16, 2021. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0248143Choudhury, Nandini, et al. Comparing two data collection methods
to track vital events in maternal and child health via community health workers in rural Nepal. *Population Health Metrics.* 2022. https://pophealthmetrics.biomedcentral.com/counter/pdf/10.1186/s12963-022-00293-4.pdf.

[18] Siyam, Amani, et al. The burden of recording and reporting health data in primary health care facilities in five low- and lower-middle income countries. *NCBI.* September 13, 2021. https://pmc.ncbi.nlm.nih.gov/articles/PMC8436492/.

data. In all countries but Nigeria, the time to complete patient health and care register information, represented **24-50%** of **total consultation time**; in some cases, time to complete register/case information **exceeded 50%** of the consultation time, with percentages varying by service area and country. Self-reported time required to complete **additional reporting forms** of **aggregated data** on a **monthly basis**, varied from **10 hours** in Nigeria to **65 hours per month** in Tanzania.[19] These sizeable burdens serve to **divert time and resources away from patient care**.

Manually-derived records have other concerns as well. For example, they often are **insufficiently standardized** and **lack integration across all services**, to address individual patient care needs throughout their lives.[20] The collection of **large volumes of data** through multiple, sometimes overlapping register and reporting forms, especially when combined with limited training and supportive supervision, are also factors contributing to **poor quality of data**, further discussed below. These collective challenges serve to undermine the utility of data for broader patient, facility, National, and sub-National consideration.[21]

b. Quality of manually-derived primary care data in LMIC settings

Beyond the time burdens of manual data collection and reporting in LMIC primary care settings, the challenge of **quality and reliability of data** collected, has also been identified in past reporting. [22] In reviewing the

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[19] Id.

[20] Id. See also, Braa, Jørn, et al. Improving quality and use of data through data-use workshops: Zanzibar, United Republic of Tanzania. *Sci ELO.* January 31, 2012. https://www.scielosp.org/article/bwho/2012.v90n5/379-384/; Lippeveld, Theo. Routine health facility and community information systems: creating an information use culture. *GHSP.* September 2017. https://www.ghspjournal.org/content/5/3/338?utm_source=TrendMD&utm_medium=cpc&utm_campaign=Global_Health%253A_Science_and_Practice_TrendMD_1.

[21] Siyam, Amani, et al. The burden of recording and reporting health data in primary health care facilities in five low- and lower-middle income countries. *NCBI.* September 13, 2021. https://pmc.ncbi.nlm.nih.gov/articles/PMC8436492/. See also, Maïga, Abdoulaye, et al. Generating statistics from health facility data: the state of routine health information systems in Eastern and Southern Africa. *BMJ.* September 28, 2019. https://gh.bmj.com/content/4/5/e001849; Bhattacharya, Antoinette Alas, et al. Quality of routine facility data for monitoring priority maternal and newborn indicators in DHIS2: A case study from Gombe State, Nigeria. *PLOS One.* January 25, 2019. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0211265; Nshimyiryo, Alphonse, et al. Health management information system (HMIS) data verification: A case study in four districts in Rwanda. *PLOS One.* July 17, 2020. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0235823.

[22] See, e.g., Choudhury, Nandini, et al. Comparing two data collection methods to track vital events in maternal and child health via community health workers in rural Nepal. *Population Health Metrics.* 2022. https://pophealthmetrics.biomedcentral.com/counter/pdf/10.1186/s12963-022-00293-4.pdf; Regeru, Regeru Njoroge, et al. 'Do you trust those data?'—a mixed-methods study

literature, we focused on manually-derived records **prepared by Community Health Workers ("CHWs")**, as a case study example. A 2021 scoping review by Basera and colleagues suggested that community-based **vital events reporting** by CHWs, though promising, tended to be suboptimal in data quality and completeness.[23] Studies in Mali, Ethiopia, and Malawi, conducted by the "Real-Time Monitoring of Under-Five Mortality" group, found that vital events data collected routinely by CHWs, varied in quality and completeness, rendering it difficult to accurately assess mortality rates at scale. CHWs' routine data underreported both births and deaths when compared to household survey estimates.[24]

Regeru and colleagues (2020),[25] researchers that have also discussed the quality of community-level health data collected and reported by CHWs, described studies in Ghana, Kenya, Malawi, Pakistan, and Rwanda that found regular under- and over-reporting by CHWs.[26] They went on to

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assessing the quality of data reported by community health workers in Kenya and Malawi. *Oxford Academic.* January 16, 2020. https://academic.oup.com/heapol/article/35/3/334/5707447.

[23] Id. See also, Basera, Tariro J., et al. Community surveillance and response to maternal and child deaths in low- and middle-income countries: A scoping review. *PLOS One.* March 16, 2021. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0248143.

[24] Choudhury, Nandini, et al. Comparing two data collection methods to track vital events in maternal and child health via community health workers in rural Nepal. *Population Health Metrics.* 2022. https://pophealthmetrics.biomedcentral.com/counter/pdf/10.1186/s12963-022-00293-4.pdf. See also, Silva, Romesh, et al. Can Community Health Workers Report Accurately on Births and Deaths? Results of Field Assessments in Ethiopia, Malawi and Mali. *PLOS One.* January 5, 2016. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0144662; Bryce, Jennifer. "Real-Time" Monitoring of Under-Five Mortality: A Vision Tempered by Reality. *PLOS One.* January 25, 2016. https://journals.plos.org/plosmedicine/article?id=10.1371/journal.pmed.1001912.

[25] Regeru, Regeru Njoroge, et al. 'Do you trust those data?'—a mixed-methods study assessing the quality of data reported by community health workers in Kenya and Malawi. *Oxford Academic.* January 16, 2020. https://academic.oup.com/heapol/article/35/3/334/5707447.

[26] Id. See also, Helleringer S, et al. Operational study of the quality of health data aggregated by community health workers in the Upper East Region of Ghana. *APHA.* November 8, 2010. https://apha.confex.com/apha/138am/webprogram/Paper219301.html; Mahmood, Shahid and Ayub, Muhammad. Accuracy of primary health care statistics reported by community based lady health workers in district Lahore. *NCBI.* August 2010. https://pubmed.ncbi.nlm.nih.gov/20726196/#:~:text=Results%3A%20Out%20of%2040%20lady,of%20reports%20were%20found%20accurate; Otieno, C.F., et al. Reliability of Community Health Worker Collected Data for Planning and Policy in a Peri-Urban Area of Kisumu, Kenya. *Springer Nature Link.* 2012. https://link.springer.com/article/10.1007/s10900-011-9414-2; Admon, A.J., et al. Assessing and improving data quality from community health workers: a successful intervention in Neno, Malawi. *Ingenta Connect.* March 2013. https://www.ingentaconnect.com/content/iuatld/pha/2013/00000003/00000001/art00016; Mitsunaga, Tisha, et al. Utilizing community health worker data for program management and evaluation: Systems for data quality assessments and baseline results from Rwanda. *Science Direct.* May 2013. https://www.sciencedirect.com/science/article/abs/pii/S0277953613001263; Otieno-Odawa, Careena Flora and Kaseje, Dan Owino. Validity and reliability of data collected by community health workers in rural and peri-urban contexts in Kenya. *Springer Nature Link.* May 12, 2014. https://link.springer.com/article/10.1186/1472-6963-14-S1-S5; Yourkavitch, Jennifer, et al. How do we

observe that low-quality data has resulted in "little demand for and use of community health information systems in decision-making."[27] Factors that were found to contribute to low-quality community-level health data in these studies, include inadequate and incompatible data collection and reporting tools; lack of training of CHWs on data management; high workload accompanied by insufficient numbers of supervisors for CHWs; and the perception of CHWs that the data they report is not used, thereby reducing motivation to manage data more stringently.[28]

These studies highlight both the importance of further addressing the **reliability** of data collected manually by CHWs, and **reducing the heavy burdens** of collecting, reporting, and maintaining manually-derived health data -- duties, which detract from patient care.

3. Digitizing LMIC healthcare infrastructure and services

Catalyzed by both the **pandemic** and by recent **global health funding disruptions**, LMICs have begun to accelerate pathways to health system self-sufficiency. **Digitization** of PHC **data** and **services** has been identified by global health authorities as an **essential feature** for LMIC **health system transformation**.[29] Among other guiding principles, the WHO has called for **commitment** by countries to support national **integrated**, **interoperable** digital health **strategies** and **architecture** for health **system strengthening**.[30] Some countries, like **India**, with its **Ayushman Bharat**

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know? An assessment of integrated community case management data quality in four districts of Malawi. *Oxford Academic.* May 9, 2016. https://academic.oup.com/heapol/article/31/9/1162/2452981.

[27] Regeru, Regeru Njoroge, et al. 'Do you trust those data?'—a mixed-methods study assessing the quality of data reported by community health workers in Kenya and Malawi. *Oxford Academic.* January 16, 2020. https://academic.oup.com/heapol/article/35/3/334/5707447. See also, Wagenaar, Bradley H., et al. Using routine health information systems for well-designed health evaluations in low- and middle-income countries. *Oxford Academic.* April 16, 2015. https://academic.oup.com/heapol/article/31/1/129/2363564.

[28] Id. See also, Ekirapa, A, et al. Data Demand and Use in the Health Sector in Central and Eastern Kenya. *Population Association.* 2013. https://paa2013.populationassociation.org/papers/132738; Yourkavitch, Jennifer, et al. How do we know? An assessment of integrated community case management data quality in four districts of Malawi. *Oxford Academic.* May 9, 2016. https://academic.oup.com/heapol/article/31/9/1162/2452981.

[29] Health and care workforce -- Global strategy on human resources for health: workforce 2030. *World Health Organization.* December 20, 2024. https://apps.who.int/gb/ebwha/pdf_files/EB156/B156_15-en.pdf. See also, Sustainable Development Goal 9: Investing in ICT access and quality education to promote lasting peace. *UN.* June 20, 2017. https://www.un.org/sustainabledevelopment/blog/2017/06/sustainable-development-goal-9-investing-in-ict-access-and-quality-education-to-promote-lasting-peace/.

[30] Id.

Digital Mission,[31] and **Kenya**, with its **"Digital Health Superhighway,"**[32] are leading by high-profile example, but they are not alone. Many LMICs, including countries most affected by recent donor aid curtailment (e.g., in SSA), have issued **policies** and/or **legislative initiatives** to **advance digitized health infrastructure and related tools**, as a threshold feature of their healthcare system "resets."[33] Those LMICs that are most boldly championing **digital health architecture and services** for system **strengthening**, are **investing** to advance this goal. These countries tend to describe National roll-out of digital health infrastructure and care, as a **"necessity"** rather than an **"option."**[34]

The **use of AI in LMIC health services** has been widely acknowledged as an important feature of digital health. Understanding its enormous potential for improving health, in 2021, the WHO launched a report on use of **AI** deployment in health service delivery and health systems more generally.[35]

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[31] National Health Authority. *Ayushman Bharat Digital Mission.* https://abdm.gov.in.
[32] Digital Health Act. *Kenya Law.* November 24, 2023. https://new.kenyalaw.org/akn/ke/act/2023/15/eng@2023-11-24. See also, Nwaononiwu, Ebubechi and Mbuthia, Boniface. Is Kenya's New Digital Health Act the Key to Smarter Health Spending? *SPARC.* October 2024. https://sparc.africa/2024/10/is-kenyas-new-digital-health-act-the-key-to-smarter-health-spending/; Kenya Takes Major Step Towards Digital Health Transformation with New Regulations. *Ministry of Health.* April 7, 2025. https://www.health.go.ke/kenya-takes-major-step-towards-digital-health-transformation-new-regulations; Kenya's Digital Health Regulations 2025: A Step Towards Transforming Healthcare. *Devdiscourse.* August 4, 2025. https://www.devdiscourse.com/article/health/3339229-kenyas-digital-health-regulations-2025-a-step-towards-transforming-healthcare; Analysing and Enhancing Digital Health Standards for Effective Digital Health Transformation in Kenya. *Transformation Health Coalition.* May 2024. https://transformhealthcoalition.org/wp-content/uploads/2025/02/Analysing-and-Enhancing-Digital-Health-Standards-in-Kenya.pdf.
[33] See, e.g., National Digital Health Strategy for South Africa -- 2019 – 2024. *National Department of Health.* https://www.health.gov.za/wp-content/uploads/2020/11/national-digital-strategy-for-south-africa-2019-2024-b.pdf; Digital Health Strategy July 2019 - June 2024. *The United Republic of Tanzania.* https://www.healthdatacollaborative.org/fileadmin/uploads/hdc/Documents/Country_documents/Tanzania/Tanzania_Digital_Health_Strategy_2019_-2024.pdf; The Uganda Health Information and Digital Health Strategic Plan 2020/21-2024/25. *The Republic of Uganda Ministry of Health.* January 2021. https://guluhospital.net/wp-content/uploads/2023/05/Health-Information-Digital-Health-Strategic-Plan_01032023.pdf; Digital-in-Health. *NDHI.* 2024. https://www.digitalhealth.gov.ng; The National Digital Health Strategic Plan -- 2018-2023. *Ministry of Health.* June 2018. https://extranet.who.int/countryplanningcycles/sites/default/files/public_file_rep/RWA_Rwanda_Digital-Health-Strategy_2018-2023.Pdf; National E-Health Strategy. *Ghana E-Health Strategy.* https://www.moh.gov.gh/wp-content/uploads/2016/02/Ghana-E-Health-120504121543.pdf; The 2020-2024 National Digital Health Strategic Plan. *Minsante.* https://www.prb.org/wp-content/uploads/2020/06/Cameroun-PLAN-STRATEGIQUE-NATIONAL-DE-SANTE-NUMERIQUE_Réduit.pdf.
[34] See, e.g., Ministry of Health Accelerates Digital Transformation in Healthcare. *Ministry of Health.* January 29, 2025. https://www.health.go.ke/ministry-health-accelerates-digital-transformation-healthcare; National Health Authority. *Ayushman Bharat Digital Mission.* https://abdm.gov.in.
[35] WHO issues first global report on Artificial Intelligence (AI) in health and six guiding principles for its design and use. *World Health Organization.* June 28, 2021. https://www.who.int/news/item/28-06-2021-who-issues-first-global-report-on-ai-in-health-and-six-guiding-principles-for-its-design-and-use.

The report gives a special nod to AI's **beneficial use in LMICs**, to **address gaps in healthcare delivery and services** when well validated and otherwise deployed to minimize risks and other concerns.

With global health aid significantly disrupted for the foreseeable future, LMICs are now at an important "pivot point," with AI-enabled digital innovation poised to **bridge gaps in access** and to help transform LMIC healthcare infrastructure into **more self-reliant** and **sustainable** service delivery systems. Among other **patient care benefits**, **digital platforms** and other forms of **innovation**, especially when augmented by **AI assistance**, can optimize clinical decision-making and related caregiving efficiencies and workflows; better allocate healthcare personnel duties, so that more time may be devoted to patient care; provide more holistic, integrated patient care management; improve patient follow-up compliance; and ultimately provide opportunities for improved patient care outcomes and lower healthcare costs.

System improvements from digitizing health records, include: optimizing work flow efficiencies; reducing the risk of error and illegible patient care entries; automating, standardizing, and otherwise improving data quality and compatibility; interoperability and related improved collaboration between care providers; and more useful aggregated population data, for policy, budgeting, and other forms of decision-making at National and sub-National levels.

Any new digital platform or intervention, including those AI-enabled, must have appropriate **performance validation** customized to **LMIC clinical contexts**.

*   *   *

The **need for solutions** to LMIC primary care personnel shortages, excessive workloads, data collection and management, and other access challenges, must now be **balanced against** the **new reality of diminished global development aid**, co-existing with the **need for more self-reliant, cost-effective system strengthening**. Healthcare digital systems and interventions, especially those AI-enabled, are receiving **heightened global attention** for their role in addressing and balancing these competing interests. Now, more than ever, **AI-enabled digital solutions** are needed to **bridge the divide** between addressing **historical** LMIC primary care

challenges on the one hand, while **catalyzing** new streamlined, **cost-effective solutions** that bring **measurable value** to primary care systems, on the other.

B. Tackling the Problem

During this last year, as most LMICs have intensified efforts to strengthen their health systems, especially with respect to primary care, Qure.ai has been at the forefront of these issues. The Company serves as an important **early example** of **private sector innovations**, addressing critical healthcare gaps and needs in LMICs, with **leapfrog digital/AI solutions** helping to transform the future of healthcare in these geographies. We summarize below the Company's new **Qure OS** digital innovation platform, and its **AIRA "**co-pilot" digital tool for healthcare workers in LMIC PHC settings.

1. Qure OS: providing a digital "sandbox" and platform to facilitate early testing and iteration of AI/digital solutions, prior to more formal pilot testing in specific LMICs

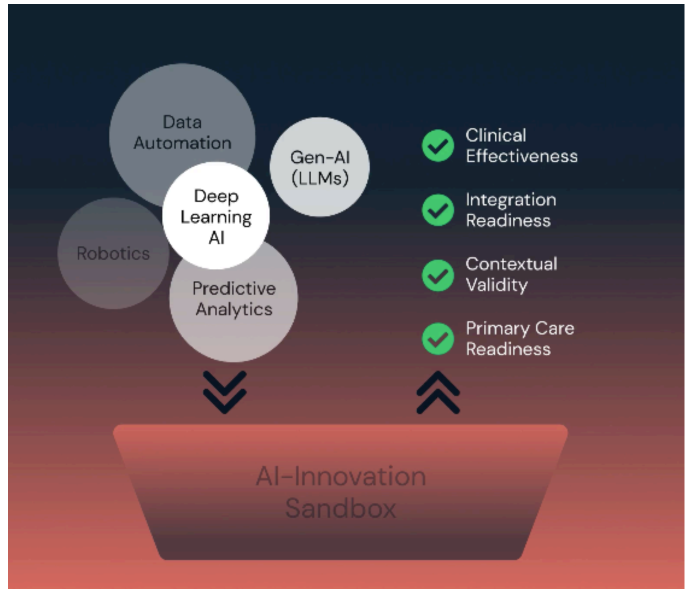
Qure OS is an LMIC-specific AI innovation **"sandbox"** and **platform**, with **three** aims in mind:

- to allow **vendors/innovators** to **test clinical and contextual validity** of their AI health tools in **any given LMIC**, before piloting them more formally in that country, thereby **reducing the innovation-to-impact turnaround time**;

- to **simplify adoption** of **AI** and similar forms of **emerging health technologies** from across the globe, for country-specific purposes in LMICs; and

- to provide a **platform** for **local innovators** to test and iterate on implementable solutions, to help strengthen their country's health system.

The **ultimate goal** of this sandbox/platform is to serve as a country's "one-stop-shop" for AI-enabled and other digital health tools. It brings together applications from proven organizations worldwide, across various disease areas, including non-communicable diseases ("NCDs"), infectious diseases, and maternal and child health, all on a single platform. It will also include a specialist AI chatbot to aid clinical decision support for PHC workers, further described below. By improving access to AI-powered digitization, PHCs can be strengthened, aiding better triage, efficient resource allocation, and improved patient care.



Examples of tools and programs that would benefit from the OS "digital virtual incubator" platform, include:

- any **Deep Learning**, **generative AI**, and/or **LLM-enabled digital tools and/or services** to help screen, diagnose, manage, or monitor diseases, including much needed tools to address the **growing burden of NCDs**;

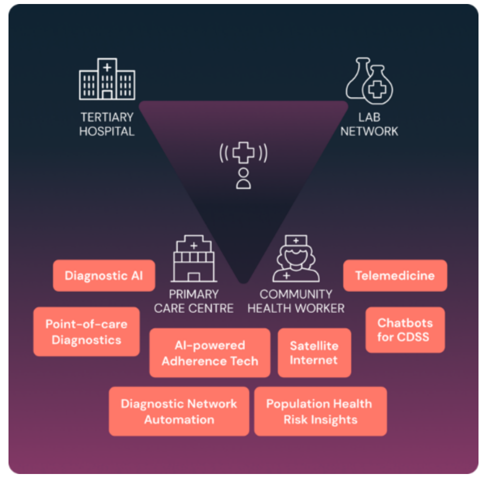
- all forms of **data automation** and other tools that render healthcare personnel more efficient and/or optimize patient care;

- clinical decision support, including tools involving **predictive analytics**;

- patient assists, including follow-up compliance monitoring programs; and

- any other digital innovations that might address the wide spectrum of PHC needs in LMICs.

With a growing partner ecosystem, including solutions for respiratory health (Alveofit), cough diagnostics (Salcit by Swaasa), and remote adherence tracking (SureAdherence), **Qure OS** supports a broad spectrum of clinical needs. From TB screening to maternal health, the platform enables faster innovation cycles by allowing institutions to pilot and validate solutions using local datasets. This sandbox approach de-risks digital adoption and creates a systematic pathway for AI integration into national programs.



Currently, Qure OS includes the following core components:

- **qTrack by Qure.ai:** A multi-disease AI-powered patient and program management platform that enables integrated service delivery, centralized case tracking, and real-time dashboards. It allows partners to monitor outcomes at both site and national levels, integrates multiple AI solutions, and supports country-level reporting with seamless workflows.

- **qXR by Qure.ai:** An advanced AI chest X-ray interpretation platform trained on **over 5M** scans from global datasets. It detects more than **30** findings including **tuberculosis, lung nodules, heart failure risk, and silicosis**. Endorsed by WHO guidelines, qXR can be used autonomously for TB screening and triage in community settings, helping bridge screening gaps in radiology-scarce regions.

- **DataToCare by Savics:** A real-time lab data integration and inventory management system that connects over **850** labs across **18** countries. It automates lab results; displays test data on dashboards; manages inventory; and sends instant alerts to patients and providers. In addition to those capacities, it works offline; supports multi-lingual interfaces; and helps optimize national lab networks.

- **SureAdherence by Dimagi:** A proven “video directly observed therapy” (“VDOT”) solution that allows patients to record medication intake via smartphone videos. Health workers can verify up to **150** videos per hour. Used in **350+** programs across **18** countries, it sustains over **90%** adherence with minimal data costs and infrastructure requirements.

- **AlveoMD by Alveofit:** A portable, AI-driven spirometry solution that helps manage asthma, COPD, and TB follow-up. Battery-operated and cloud-connected, it measures key lung function parameters, integrates with dashboards, and is ideal for rural and mobile outreach. It is low-cost, requires minimal training, and aligns with WHO-integrated respiratory care frameworks.

- **Salcit by Swaasa:** A smartphone-enabled AI tool that analyzes cough sounds to identify at-risk patients. It supports early screening for respiratory conditions, optimizes triage workflows, and enhances diagnostic yield. This solution is particularly effective for community health workers operating in resource-limited field settings.

The broader impact of Qure OS lies in its ability to unify these point solutions under a single, interoperable platform that can be quickly localized, rapidly deployed, and scaled across geographies. With proven AI tools already embedded, **Qure OS** lowers barriers to adoption, enhances data consistency across care pathways, and helps national stakeholders make evidence-based investment and policy decisions. Going forward, Qure OS' digital health architecture will evolve with local needs and ensure global innovations translate into meaningful on-the-ground impact.

2. AIRA: Qure.ai's AI "co-pilot" tool for health workers in LMIC primary care settings

Launched at the World Health Assembly 2025, AIRA is Qure.ai's AI-powered digital assistant built specifically for LMIC primary health systems. Designed to multiply the impact of every health dollar and accelerate progress towards universal health coverage, AIRA reduces administrative burdens, supports clinical decision-making, and generates actionable insights for health authorities at the policy level.

Trained on local health data, it features built-in localization, seamless interoperability, and a clinician-first design to meet real-world needs. AIRA automates clinical note-taking, guides protocol-based care, and generates real-time insights without disrupting clinical workflows. It supports a wide range of disease areas, adapts to local contexts, and integrates directly into existing digital systems. Here is a sampling of its capacities:

(a) **Automated voice and image-based data capture:** AIRA captures patient symptoms and history using spoken language and visual cues, removing the need for manual entry, while improving accuracy, and helping to reduce documentation time and error rates.

(b) **Intelligent, passive-first engagement:** AIRA operates in the background and intervenes only when contextually relevant, minimizing interruptions during clinical care, ensuring a smooth and non-intrusive experience for health workers.

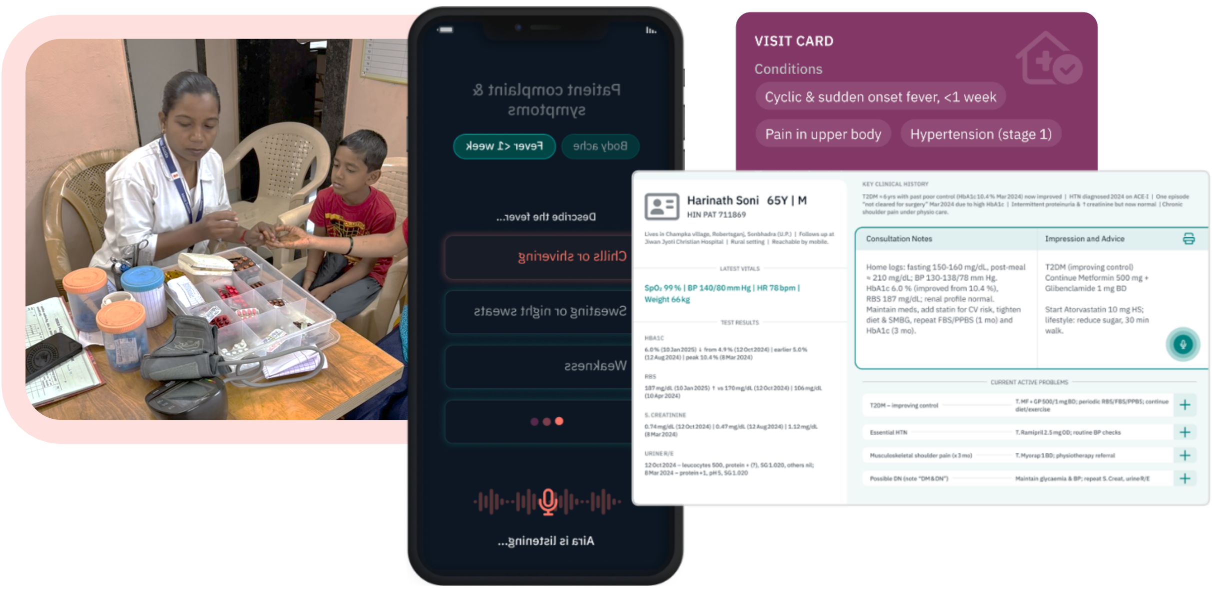
(c) **Clinical protocol adherence and clinical decision support**: AIRA is intended to help healthcare workers follow guidelines and make informed decisions, especially in resource-constrained settings.

(d) **Aggregating population health insights**: AIRA aims to overcome the steep burdens and current limitations of manually-derived monthly reports, prepared by PHC workers for use by health authorities. Automation and standardization should help provide countries with improved understanding of population health trends, and facilitate informed policy and funding decisions for population health.

(e) **On-demand upskilling through built-in guidance:** AIRA delivers expert decision support through embedded clinical logic, empowering non-specialist staff to provide higher quality care with confidence.

(f) **Locally adapted performance:** AIRA is tailored to local disease burdens, protocols, and infrastructure, ensuring relevance and cultural sensitivity, making it suitable for deployment across diverse settings.

(g) **Seamless integration with national digital systems:** AIRA interfaces with EMRs and health information systems, automatically populating structured fields to avoid redundant documentation, and streamlining workflows and data entry.



(h) **Technology and Privacy**

AIRA supports over **100** languages, including key **African** and **Asian** dialects like **Swahili**, **Yoruba**, and **Hindi**, with localized adapters ensuring transcription accuracy. It is cloud-first for rapid deployment and real-time updates, and an offline-ready version is also in development for low-connectivity areas. Designed with privacy at its core, AIRA activates only with clinician consent, captures only clinically relevant data, and fully aligns with global data protection standards like the European Union's General Data Protection Regulation ("GDPR").[36]

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[36] General Data Protection Regulation, https://gdpr-info.eu.

AIRA represents a significant leap forward in digital health for LMICs, not just by automating routine tasks, but by fundamentally reshaping how frontline care is delivered and managed. Its thoughtful design ensures that technology enhances, rather than disrupts, clinical workflows, making it easier for health workers to focus on patients. By prioritizing local adaptation, robust privacy standards, and broad language support, AIRA demonstrates how AI can be responsibly scaled to meet the diverse needs of global health systems. Ultimately, AIRA empowers both clinicians and health leaders with actionable insights, helping drive systemic improvements and accelerating progress towards more equitable, efficient, and data-driven healthcare.

Both AIRA and Qure OS have garnered significant interest and are currently in active planning and collaboration phases for deployment across LMIC settings. As part of development and validation, the technology **AIRA** has been implemented in PHC settings in both **India** and **Nigeria**. **AIRA** has also been tested in **Rwanda**, and the Company is in active discussions with institutions in that country to initiate pilots and generate contextual evidence. In India, engagements are underway with multiple State governments to pilot the solution across public healthcare facilities and evaluate **AIRA's** impact. **Africa** continues to remain a key priority for implementation, with ongoing efforts focused on delivering tangible health system strengthening outcomes and enabling digital transformation at scale through strategic partnerships and aligned implementation pathways.

II. IMPACT SPOTLIGHT TWO:

Redefining Early Lung Cancer Detection in LMICs: Qure.ai's Scalable, AI-Driven Approach

A. Background

Lung cancer remains the leading cause of cancer-related deaths globally, accounting for approximately 1.8 million deaths in 2022, with 2.4 million new cases reported in 2022 alone.[37] While the majority of lung cancer cases have historically occurred in high-income countries ("HICs"), the burden is increasing rapidly in low- and middle-income countries ("LMICs") due to rising rates of air pollution (both indoor and outdoor), occupational hazards, and in some regions, tobacco use.[38,39,40]

Despite this rising burden, early detection remains extremely limited in LMICs, where access to advanced imaging modalities such as CT scans and structured screening programs is often lacking.[41] This results in most patients being diagnosed at late stages, when treatment options are more expensive and survival outcomes are poor. Studies have shown that early-stage detection of lung cancer can increase five-year survival rates from **<20%** to **>60%**,[42,43] yet achieving this requires scalable, cost-effective, and accessible screening approaches tailored to LMIC healthcare systems.

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[37] Ferlay J, Ervik M, Lam F, Laversanne M, Colombet M, Mery L, Piñeros M, Znaor A, Soerjomataram I, Bray F. Global Cancer Observatory: Cancer Today. Lyon, France: International Agency for Research on Cancer. A.

[38] Gordon SB, Bruce NG, Grigg J, et al. Respiratory risks from household air pollution in low and middle income countries. Lancet Respir Med. 2014;2(10):823-860.

[39] Hashim D, Boffetta P. Occupational and environmental exposures and cancers in developing countries. Ann Glob Health. 2014 Sep-Oct;80(5):393-411.

[40] Shankar A, Saini D, Dubey A, Roy S, Bharati SJ, Singh N, Khanna M, Prasad CP, Singh M, Kumar S, Sirohi B, Seth T, Rinki M, Mohan A, Guleria R, Rath GK. Feasibility of lung cancer screening in developing countries: challenges, opportunities and way forward. Transl Lung Cancer Res. 2019 May;8(Suppl 1):S106-S121.

[41] Jiwnani S, Penumadu P, Ashok A, Pramesh CS. Lung Cancer Management in Low and Middle-Income Countries. Thorac Surg Clin. 2022 Aug;32(3):383-395. doi: 10.1016/j.thorsurg.2022.04.005. PMID: 35961746.

[42] Siegel RL, Kratzer TB, Giaquinto AN, Sung H, Jemal A. Cancer statistics, 2025. CA: A Cancer Journal for Clinicians 2025; 75: 10–45.

[43] Aberle DR, Adams AM, Berg CD, et al. (2011). Reduced Lung-Cancer Mortality with Low-Dose Computed Tomographic Screening. **N Engl J Med.** 365:395–409.

B. Tackling the Problem

qXR-LN ("for Lung Nodules"): A Scalable Solution for Early Detection

Over the past year, Qure.ai has significantly expanded, and generated rigorous data to support, use of qXR-LN[44] across diverse healthcare settings. Through strategic partnerships, the Company is building a strong foundation for scalable, sustainable early detection in LMICs -- one that is evidence-based, cost-effective, and inclusive of high-risk, underserved populations such as never-smokers and younger adults.

As many LMICs intensify efforts to strengthen their health systems, Qure.ai has been at the forefront of this shift, demonstrating how private-sector innovation can help close critical diagnostic gaps. Its AI-driven solutions are not only transforming how lung cancer is detected, but also redefining what is possible for health systems operating under resource constraints.

Key Highlights: Evidence of Impact and Scalability

1. Over 5 Million Screenings Across 20+ Countries

In partnership with AstraZeneca, Qure.ai has screened over **5 million** chest X-Rays in more than **20** countries, identifying **high-risk nodules** in nearly **50,000** individuals, each flagged for follow-up testing and potential diagnosis. This scale of implementation showcases the feasibility of integrating AI-driven screening into National health systems.

2. Multi-country validation of qXR LNMS ("Lung Nodule Malignancy Score")

CREATE (NCT05817110) is a prospective, observational trial conducted across **5 countries** to validate the performance of qXR-LN's AI-based Lung Nodule Malignancy Score for detecting high-risk incidental pulmonary

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[44] AI-powered software designed to aid in the detection of pulmonary nodules on chest X-rays.

nodules ("IPN") on chest X-Rays. **Over 700** participants older than 35 years and having pulmonary nodules (nodule size between 8 mm and 30 mm) were enrolled across **Egypt**, **India**, **Indonesia**, **Mexico**, and **Turkey**. The findings, presented at the **2024 European Lung Cancer Congress**, provide robust evidence of the tool's clinical performance across diverse LMIC settings.

> --Positive Predictive Value ("PPV"): 54.2% (vs. pre-defined threshold of success of 20%)
>
> --Negative Predictive Value ("NPV"): 93.5% (vs. pre-defined threshold of 70%)

qXR showed a PPV of 54%, meaning when it flagged a case having a nodule with high malignancy risk, the same was confirmed on CT more than half of the time. qXR showed a NPV of 94%, meaning it was very reliable when identifying low-risk cases.[45]

These results exceed the thresholds and were consistent across **key underserved groups**, such as **never-smokers and individuals under 55**, who are typically excluded from conventional screening programs. A key insight from the field screening data was that **70% of 510 never-smoker patients** tested were identified as **higher-risk** based on qXR LNMS scores, highlighting the tool's capacity to detect cancer risk in populations that would otherwise go unnoticed. This study has been submitted for publication.

The increasing global burden of lung cancer among never-smokers, especially among **women**, has received considerable attention in the public health literature.[46] Peer reviewed by experts at the Congress, the CREATE

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[45] Together, these LNMS performance specifications, loosely translated, mean a very robust performance to prevent the risk of false negatives (mistakenly not finding a malignancy), and a reasonably good measure of true positives for its intended purpose -- as an early screening system to optimize the number of subsequent, more costly referrals to CT diagnostic tests, for those truly in need.

[46] See, e.g., LoPiccolo, Jaclyn, et al. Lung cancer in patients who have never smoked — an emerging disease. *NCBI.* April 12, 2024. https://pmc.ncbi.nlm.nih.gov/articles/PMC11014425/; Jani, Chinmay T., et al. Evolving trends in lung cancer risk factors in the ten most populous countries: an analysis of data from the 2019 Global Burden of Disease Study. *The Lancet.* January 9, 2025. https://www.thelancet.com/action/showPdf?pii=S2589-5370%2824%2900612-6; Cheng, Elvin S., et al. Lung cancer risk in never-smokers: An overview of environmental and genetic factors. *NCBI.* October 31, 2021. https://pmc.ncbi.nlm.nih.gov/articles/PMC8580800/; Shanker, Abhishek, et al. Environmental and occupational determinants of lung cancer. *NCBI.* May 2019. https://pmc.ncbi.nlm.nih.gov/articles/PMC6546634/.

findings confirm that qXR LN can accurately identify high-risk individuals across diverse demographic and risk profiles, broadening the reach of early detection strategies and making them more inclusive.

3. Health Economics Modeling: Cost-Neutral at Scale

As LMICs move to **reframe their budgets** with **less global aid**, they increasingly are looking to set **fiscal health priorities** and **to examine** the **economic impact** of specific proposed **health budget expenditures**. To support health system decision-making, **Budget Impact Models ("BIMs")** were developed, specifically tailored to LMIC settings. Qure.ai first developed BIM for Vietnam, and now has additional studies underway for other LMICs, to support inclusion of qXR-LM in those countries' National health budgets as well.

The BIM for Vietnam aimed to determine the impact on Vietnam's health budget, of implementing AI at a population level for incidental pulmonary nodule detection.[47] Budget Impact Modeling with a **time horizon** of **five years** was developed, comparing the implementation of qXR to the country's current diagnostic process. A decision-tree design was used to determine the number of patients identified by qXR and their stage at diagnosis, while the **National incidence** and **stage distribution** were used for the country's "current diagnostic process."

Results:

- qXR implementation was projected to identify an additional **3,155** lung cancer cases, largely due to earlier detection.
- As a result, **4,742 premature deaths** were **prevented** across the **5-year time frame**.
- **Stage shift:** A higher proportion of cases were diagnosed at **Stage I** or **II**, where **treatment** is **more effective** and **less costly**.
- **Cost trajectory:** Initial implementation increased Year 1 health spending due to more follow-up diagnostics and earlier treatment. However, **subsequent years saw a reduction in treatment costs**, as fewer patients progressed to advanced disease. By **Year 5**, the

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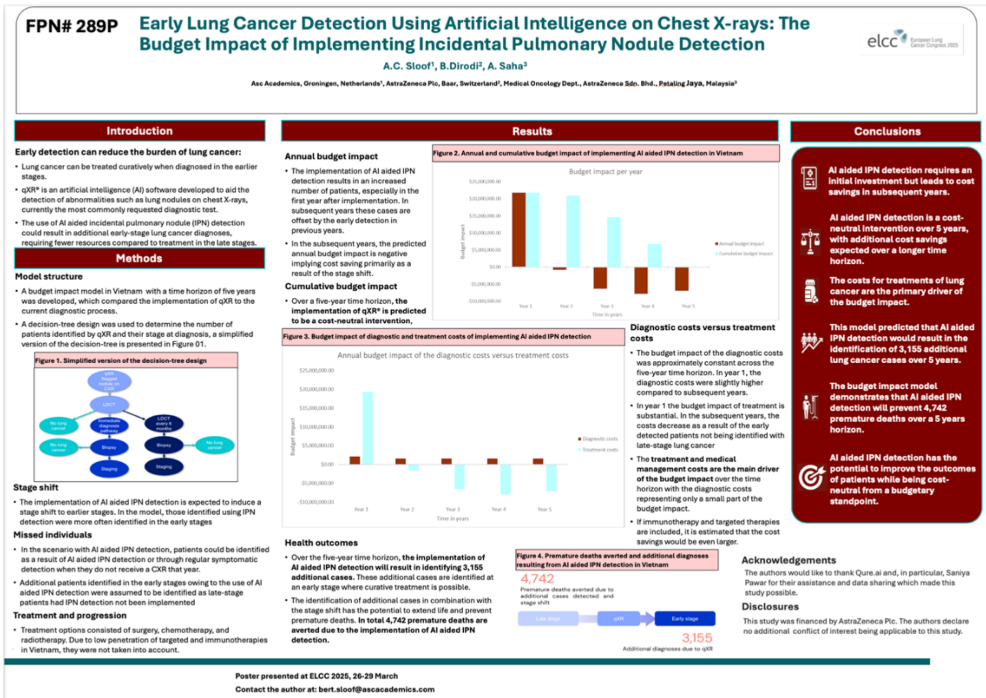
[47] Sloof, B., et al. Early lung cancer detection using artificial intelligence on chest X-rays: The budget impact of implementing incidental pulmonary nodule detection. *JTO.* March 2025. https://www.jto.org/action/showPdf?pii=S1556-0864%2825%2900481-2.

additional upfront investments were **completely offset**, making the intervention **cost-neutral** over the modelled period.

The poster presentation of this modeling in Vietnam was shown at the American Thoracic Society ("ATS") International Conference 2025, and may be seen below and reviewed more granularly here, here.



The study provided a compelling case for integrating qXR-LN into Vietnam's National health strategy, especially for programs targeting Universal Health Coverage and early cancer detection. The results suggest that investment in AI screening does not strain limited health budgets over time, and may ultimately yield long-term cost savings by reducing the burden of advanced disease.

Going forward, this Budget Impact Modeling approach will be used to assess the budget impact of qXR-LN in other LMICs. Each Model will be tailored to **country-specific** lung cancer burdens and National **expenditures** for their **existing diagnostic processes**. Current modeling studies are underway for **Costa Rica**, **Turkey**, **Thailand**, and **Colombia**.

4. Real-World Patient Stories: Putting a Human Face to the Data

Clinical numbers are only part of the story. Case reports from the field illustrate the human impact of qXR's early detection.

Take Joby, a 39-year-old truck driver from Kerala with no history of smoking or family cancer.[48] What seemed like a minor cough turned into a life altering discovery when qXR's AI-powered screening solution flagged a suspicious nodule on his X-ray. This story, also presented at the ATS International Conference this year, emphasizes the importance of incidental, early risk detection, giving Joby the chance to fight back against the disease. Through timely intervention, Joby's case shows how AI solutions like Qure's qXR can offer hope, even for those without traditional risk factors.

Click here to watch the full conversation between Dr. Prince Franko, Chief Medical Officer at Idukki (Kerala, India), and Joby, as they discuss how qXR LN helped detect Joby's lung cancer.

C. Looking Ahead: Scaling Access and National Adoption in Multiple LMICs

Qure.ai continues to expand access to early lung cancer detection through AI-driven tools tailored to LMIC healthcare systems. The Company is

[48] Franco P.C, et al.Artificial Intelligence (AI)-powered Chest X-ray in Primary Care Accelerates Time to Lung Cancer Diagnosis. *ATS*. May 2025. https://www.atsjournals.org/doi/10.1164/ajrccm.2025.211.Abstracts.A7972.

building government partnerships, generating country-specific clinical and economic data, and aligning with National strategies, to support early diagnosis and improve outcomes.

These efforts are already translating into real-world adoption. In **El Salvador**, a Digital Health Cooperation Agreement between AstraZeneca Central America and the Caribbean (“CAMCAR”) and the Government of El Salvador, marked a major milestone. El Salvador became the first country to implement **a nationwide AI-led lung cancer detection program**, deploying qXR in **30** hospitals to analyze X-rays (covering **90%** of CXRs in the **public health system**) and CT scans. This system aims to improve early risk identification, optimize care for high-risk patients, and reduce unnecessary procedures.

In **Malaysia**, Qure.ai and AstraZeneca have partnered with the Ministry of Health under the Lung Health Initiative (“LHI”) to launch a nationwide lung cancer screening program. The initiative, co-hosted with the National Cancer Society of Malaysia (“NCSM”), was themed “United by Unique” to reflect a shared focus on innovation and patient care. By integrating qXR into National screening, Malaysia is advancing early detection and tackling late-stage diagnoses more effectively.

These partnerships highlight the increasing role of AI in National healthcare planning. By embedding qXR into public health systems, countries are taking concrete steps toward scalable, efficient, and inclusive lung cancer screening.

D. Conclusion: A Scalable and Sustainable AI Solution for Early Detection

Qure.ai’s work in lung cancer screening reflects a shift in how early diagnosis can be delivered in low-resource settings. Evidence from large-scale screenings, clinical validation studies, health economic modeling, and case reports, shows that qXR-LN can help in enabling early diagnoses, improved outcomes, and scalability.

As noted, earlier-stage diagnoses have included even those populations typically excluded from traditional screening, like **never-smokers** and **younger adults**. Budget Impact Modeling, such as the Vietnam model, further shows that implementing qXR can be cost-neutral within five years, and deliver cost savings in subsequent years, while preventing thousands of premature deaths.

With El Salvador and Malaysia now adopting qXR in National programs, Qure.ai is proving that AI-based screening is not just effective, but also ready for real-world, country-level integration. As LMICs seek cost-effective, high-impact health solutions, qXR-LN offers a practical and inclusive tool to close gaps in early cancer detection and improve patient survival, where it is needed most.