ecdpm

Funded by the European Union

DISCUSSION PAPER No. 394

Realising the potential of AI for diagnostics in Africa: From barriers to scalability

By Philomena Apiko and Melody Musoni

September 2025

African policymakers and decision-makers are exploring how artificial intelligence (AI) can strengthen the health sector, reinforced by policy measures designed to support the growth of the AI innovation ecosystem. At the same time, researchers and innovators across the continent are increasingly developing AI solutions to address Africa's health challenges. In this paper, we examine AI use cases in medical imaging for diagnosing Africa's prevalent diseases – tuberculosis, malaria and cancer – as well as in prenatal and maternal diagnostics.

We find that AI plays a critical role in addressing a wide range of challenges in the healthcare sector. Some emerging AI use cases place a strong focus on inclusive healthcare and addressing health disparities. This is driven by African policymakers' firm position in global AI policy discussions, calling for ethical AI development to address both health and technology disparities. Yet, significant barriers remain, particularly in developing adequate regulatory frameworks and encouraging sufficient investment in AI infrastructure.

Regulatory challenges can be addressed by updating data laws, creating health data-sharing frameworks, and establishing ethical and legal AI governance mechanisms. Targeted funding is needed for data centers, computing facilities, hospital system integration, digital health records, cybersecurity and workforce training. In addition, verification and certification of AI in diagnostics remain limited and need to be strengthened. Finally, Europe-Africa partnerships could provide targeted support for AI in diagnostics (and healthcare generally), such as investment in digital and AI infrastructure and strengthening capacity in health regulations and ethical guidelines.

Table of contents

Acknowledgements

The authors would like to thank Chloe Teevan and Pauline Veron for their invaluable input and constructive feedback and Joyce Olders for layout and formatting. The views expressed in this note are those of the authors and do not represent those of ECDPM or any other institution. Any errors or omissions remain the responsibility of the authors. For comments and feedback, please contact mmu@ecdpm.org, pha@ecdpm.org or cte@ecdpm.org.

Acronyms

AFDB	African Development Bank
AI	Artificial Intelligence
AMR	Antimicrobial Resistance
AU	African Union
AUDA-NEPAD	African Union Development Agency – New Partnership for Africa's Development
CAD4TB	Computer-Aided Detection for Tuberculosis
CDC	Centre for Disease Control and Prevention
CDSS	Clinical Decision Support Systems
CE	Conformité Européenne (European Conformity marking)
CT	Computed Tomography
DDSS	Diagnostic Decision Support Systems
DR Congo	Democratic Republic of Congo
EU	European Union
FDA	Food and Drug Administration (USA)
HIV/AIDS	Human Immunodeficiency Virus / Acquired Immunodeficiency Syndrome
HPV	Human Papillomavirus
KEMRI	Kenya Medical Research Institute
LMIC	Low- and Middle-Income Country
MoU	Memorandum of Understanding
MRI	Magnetic Resonance Imaging
NCD	Non-Communicable Disease
SSA	Sub-Saharan Africa
TB	Tuberculosis
UNESCO	United Nations Educational, Scientific and Cultural Organisation
WHO	World Health Organization

Introduction

The development and adoption of Artificial Intelligence (AI) is expanding rapidly worldwide. For Sub-Saharan Africa (SSA), AI presents a unique opportunity to accelerate its social and economic growth. African countries are prioritising the development of AI use cases (AI solutions addressing specific problems) in key sectors such as healthcare, education, and agriculture with the expectation that the success of these AI use cases can accelerate the broader adoption of the technology across other industries.

This policy brief focuses on AI's role in healthcare, particularly in medical diagnostics, to enhance accuracy, efficiency, patient care and inclusive access by previously marginalised communities. AI-driven technologies improve diagnostics, treatment and patient monitoring while optimising decision-making and operational workflows. This technology can substantially improve healthcare research and outcomes by yielding more precise diagnoses and facilitating personalised treatment regimens. AI's capacity to rapidly analyse extensive volumes of clinical documentation aids medical professionals in identifying disease markers and trends that might otherwise go unnoticed.

Given the persistent challenges in SSA's diagnostic landscape, this paper highlights the potential of AI-driven solutions in diagnostics, especially in medical imaging, telemedicine and decision support tools. Beyond showcasing the use cases applicable to diagnostics, the paper also explores the existing challenges and barriers in the uptake of AI in health. These impediments are attributable to deficits in digital and AI infrastructures, data unavailability, security vulnerabilities, resource constraints, regulatory ambiguities, inadequate internet connectivity, and digital literacy disparities, thereby contributing to the protracted integration of AI within healthcare systems in SSA (Ephraim et al. 2024). The paper proposes concrete ways by which AI can be leveraged and scaled up to improve diagnostics and transform healthcare in SSA. The paper further scopes new opportunities for partnership and cooperation between Europe and Africa especially on AI use in the healthcare sector.

1. State of healthcare in Africa

1.1 Escalating health needs

Africa faces a growing health crisis, burdened by both infectious and non-communicable diseases (NCDs). HIV/AIDS, tuberculosis, and malaria remain the most prevalent, with antimicrobial resistance (AMR) worsening due to high infection rates, poor regulation, and limited treatment alternatives (Kariuki et al. 2022). NCDs, including cancer, are rapidly rising, now accounting for 37% of deaths in SSA (WHO, 2021). The continent also battles with frequent outbreaks of Ebola, Yellow fever, Lassa fever, M-pox, as well as neglected tropical diseases which predominantly affect impoverished communities and disproportionately impact women and children (WHO, 2023). Persistent challenges include high maternal and child mortality, gaps in sexual and reproductive health services, weak routine immunisation, and inequitable vaccine access.

The COVID-19 pandemic exposed fragile health systems characterised by poor emergency preparedness, limited infrastructure, shortages of medicines, diagnostics, and essential health equipment. The region's healthcare workforce is critically undersupplied, with only 1.55 health workers (physicians, nurses, and midwives) per 1,000 patients, well below the WHO-recommended 4.45 per 1,000 (Ahmat et al. 2022). Staffing shortages and unequal distribution of personnel further limit access to specialised care.

Compounding these challenges is a decline in international aid as seen in the recent pause in aid under the Trump administration, as well as cuts in aid funding by some European states, jeopardising the sustainability of health programmes. Without renewed investment and innovative approaches, including leveraging AI, the continent risks severe human and economic costs from failing to meet global health goals.

1.2 State of diagnostics and Africa's response

Due to the current state of healthcare, there is a significant strain on healthcare resources in Africa. The growing population, AMR, increased cross-border health risks and climate change continue to strain healthcare resources. Rapid, affordable and accessible diagnostic tools are critical but remain scarce, costly, and concentrated in urban areas. Local production of diagnostic tests and equipment is minimal, skilled personnel are lacking, and regulatory approval processes for diagnostics equipment are slow and fragmented – sometimes taking up to a decade (Africa CDC). The existing laboratory networks are underdeveloped, diagnostic imaging data is scarce, and access remains inequitable, especially at the level of primary health care, where only 19% of populations in low- and lower-middle-income countries (LMICs) have access to basic diagnostics beyond HIV and malaria testing (Fleming et. al 2021). Even in hospitals, access ranges between 60–70%, with rural and marginalised populations facing the most severe gaps.

In response to these inadequacies, the Africa Centres for Disease Control and Prevention (Africa CDC) and its partners launched the Africa Collaborative Initiative to Advance Diagnostics (AFCAD).[1] The role of AFCAD is to support endeavors that will empower all member states to attain equitable access to essential diagnostics by utilising technological advancements delivered through optimised integrated laboratory networks (AU, 2018). Priorities include accelerating regulation to facilitate timely and wide access to essential diagnostics, market interventions towards affordability and advocacy for appropriate investments in diagnostics. Though it has been seven years since the initiative was launched, there has been slow progress in increasing access and uptake of diagnostic tools in Africa. Reasons include the absence of essential infrastructure, basic equipment and supplies, skilled workforce, problems of supply chain management, equipment maintenance, lack of national standards for testing, inadequate quality management systems and biosafety measures (WHO, 2023).

AI provides the potential to address some of the access-related challenges to diagnostics on the continent. However, its adoption and scale in healthcare is influenced by a myriad of multi-factor issues including policy frameworks, regulations and ethical considerations over health data as discussed in the next section.

2. AI ethics, policy and regulation in Africa

2.1 AI policy influencing AI adoption in healthcare

Africa's AI policy development is shaped by the need to prevent digital exploitation, reduce reliance on foreign technologies, and build local AI innovation using African-specific datasets. Policymakers recognise that foreign AI tools, trained predominantly on Western data, often fail when applied to African populations, leading to inaccurate diagnoses and treatments (Victor, 2025). Moreover, ignoring local epidemiological, social, and economic contexts risks exacerbating health inequalities.

[1] Other diagnostic initiatives at the continental level include: in 2023, the Africa CDC and AUDA-NEPAD established the Diagnostic Advisory Committee (DAC) to harmonise regulatory processes for In Vitro Diagnostics (IVDs) and accelerate access. Key partners include the African Medicines Agency (AMA) and the African Medical Device Forum (AMDF), which since 2012 has worked to align medical devices regulations based on the WHO Global Model Regulatory Framework for Medical Devices.

The African Union (AU) has established several frameworks and initiatives to drive AI adoption in healthcare, ensuring structured and secure digital health advancements. The AU Digital Transformation Strategy for Africa (DTS), highlights digital health as a transformative sector, promotes interoperability, leadership and ICT-health sector collaboration. The DTS is bolstered by the Africa CDC's Digital Transformation Strategy which fosters local digital health innovation, secure data sharing, and regulatory sandboxes for AI testing. The AU Continental Strategy on AI focuses on deploying AI solutions across different sectors tailored to Africa's problems including healthcare challenges, in infectious diseases, maternal and child health, and NCDs. Additionally, the AUDA-NEPAD White Paper on Responsible AI emphasises support for AI start-ups, research centers, and innovation ecosystems. The AU Data Policy Framework provides guidance on the collection, use, sharing and storage of data. However, given the sensitivities of health (see section 2.3), calls have emerged for a health-specific data categorisation and cross-border data-sharing framework (Musoni et al. 2024) and modernisation of the Malabo Convention to address the complexities of personal data governance.

African policymakers have been quite responsive to the benefits of AI and expressed their political commitment in supporting the adoption of AI in healthcare even at country level. For example Rwanda's Digital Health Strategic plan (2018-2023) and SmartRwanda Masterplan are facilitating healthcare delivery via digital platforms. South Africa also developed its National Digital Health Strategy to promote healthcare delivery through digital innovation. Across several African countries, various policy interventions are being developed to focus on creating an enabling environment for AI innovation, building infrastructure, attracting investments, developing AI skills[2] and strengthening data governance. Nigeria National AI Strategy mirrors the AU's strategy on prioritising 'local-first' AI innovation to address Africa's unique challenges. Notable progress is being seen especially on infrastructure development, with expanded internet access, 5G rollout, building of data centers, high performance computing facilities, and diversified energy sources such as through solar to address electricity shortages.

Countries are also implementing public-private partnerships, to support digital health and AI in health solutions. For instance, Rwanda has concluded a memorandum of understanding (MoU) between its Ministry of Health and Babyl for the Digital-First Integrated Care project, improving access to healthcare in remote areas.

[2] Senegal, for instance, aims to train 90,000 AI professionals by 2028 through AI training platforms such as those offered by Senegal AI Hub (Senegal National AI Strategy).

2.2 AI Regulation

Regulating the development and use of AI technology is imperative due to the possible risks and the need to strike a balance between technological advancement, public safety, data privacy, and equity (Dominic, 2025). Africa lacks a dedicated AI legal framework, while some countries have developed a national AI strategy or AI policy,[3] no country has enacted a sui generis AI law, leaving populations vulnerable to AI systems developed without ethical safeguards, security measures, or privacy protections for health data. In the absence of AI-specific laws, data protection laws play a key role, as many African nations classify health data as sensitive and impose strict processing regulations (Townsend et al. 2023). The Malabo Convention provides continental data governance, and over 34 African countries have national data protection laws, yet these laws remain outdated and insufficient in addressing AI-specific challenges, such as accountability, third-party access to health data, and the use of foreign cloud services (Interviews 2025).

In comparison to vaccines and medicines, the regulatory frameworks for medical devices remain weak in Africa (Townsend et al. 2023). AI as a medical device poses unique regulatory challenges, such as bias, generalisability, adaptability, explainability, interpretability, accountability, and transparency.[4] For example, transparency remains a key factor given concerns around the "black-box" problem, which is the opacity of how AI makes decisions (Kiseleva et al. 2022). To date, there is no harmonised global standard or body that specifically regulates the use of AI as a medical device (Guo and Morio, 2024). In lieu of this, international organisations, national regulatory bodies, and industry associations are striving to develop common regulatory practices by adapting existing medical device regulations. For example, the WHO has developed a framework for training, validation and evaluation of AI-based medical devices, which looks at both the development and post-surveillance once AI software has been launched into the market. Within the continent, the African Medical Devices Forum, tasked with aligning medical devices regulations and diagnostics regulation has yet to provide regulatory guidance for the use of AI in clinical healthcare and research. At the national level, an analysis of statutes governing medical devices in the 12 select African countries[5] showed that no legislation explicitly mentions AI or

[3] These include South Africa, Egypt, Kenya, Nigeria and Rwanda.

[4] AI bias refers to the differential performance, leading to perpetuation and worsening health inequalities. Lack of generalisability means an algorithm performs poorly when deployed in new settings. Interpretability is the extent to which a user understands how an algorithm produces output and can challenge decisions arising from output. Explainability refers to how an AI/ML and its output can be explained in a way that makes sense to a human being at an acceptable level.

[5] Botswana, Cameroon, The Gambia, Ghana, Kenya, Malawi, Nigeria, Rwanda, South Africa, Tanzania, Uganda, and Zimbabwe.

algorithms within the definition of a medical device (Townsend et al. 2023). As such, countries will have to update their regulatory frameworks to provide an enabling environment for the development and scaling of AI in health/diagnostics.

2.3 Ethical considerations over health data

Global health disparities shape AI deployment in Africa, often to the detriment of local populations due to biases in training data predominantly sourced from the Global North. African health conditions remain underrepresented in AI healthcare tools, leading to inaccuracies and potential misdiagnoses. Biases in facial recognition and generative AI models further highlight these gaps, with non-inclusive datasets limiting their effectiveness in African contexts (Nsoesie, 2024) including by underrepresenting African health conditions (Sekati, 2025). Language barriers also hinder AI-driven telemedicine and diagnostics, as large language models (LLMs) primarily cater to English and other widely spoken Global North languages, excluding many African communities (Mateen, 2024). As a result, these tools may not effectively serve community health workers or patients in African communities where English is not the primary language (PATH, 2024). Additionally, informed consent and transparency in AI in healthcare remain complex issues, necessitating clear communication with patients about the use of their data, especially with AI algorithms that may be challenging for non-experts to understand. This includes detailing data sharing implications, potential benefits and risks associated with AI-driven healthcare, and the level of human oversight in AI decisions (Varnosfaderani and Forouanfar, 2024) to address issues of accountability for misdiagnosis.

As discussed, policies, regulations and ethical considerations over health data are important factors that are influencing AI adoption in healthcare, which have to be carefully balanced against the potential benefits of AI. Studies have shown numerous benefits of AI in diagnostics for equitable and inclusive healthcare including reaching underserved populations, which are discussed in the next section.

3. AI opportunities for equitable and inclusive healthcare

3.1 Improving access to diagnostics for marginalised populations

Timely access to diagnostics remains a challenge in many African countries due to the cost and distance to testing centres or lack of skilled personnel, equipment or laboratory facilities. AI-driven diagnostics are democratising healthcare by making early and accurate diagnoses more accessible, especially in regions with limited access to specialised medical professionals. Given the shortages of skilled health workers in SSA, AI-powered clinical tools could represent one way to increase quantity and quality of medical care (Ciecierski-Holmes et al. 2022).

However, the proliferation of AI tools in healthcare also risks increasing the potential for AI to exacerbate existing inequalities in healthcare. Due to infrastructure challenges, the majority of AI solutions mostly function in urban areas, or areas with internet coverage and steady power supply, leaving out remote areas. Some of the AI solutions predominantly use the English language and do not use local languages. These limitations lead to AI divides where several groups of people are marginalised due to lack of access to the internet, digital devices, language barriers and lack of affordability. As discussed under section 4, most of the selected AI use cases are being designed with the aim of closing these divides and promoting inclusive AI adoption by reaching underserved populations. However, these efforts are not happening fast enough to close the AI gaps, necessitating a comprehensive approach to ensure that AI in diagnostics is developed taking into account these socio-economic contexts and localisation needs. Future advancements of AI in diagnostics should emphasise the development of more inclusive AI models that cater to a broader patient demographic, ensuring equitable healthcare improvements across all populations.

Box 1: Reducing health disparities using AI

Challenge	Solution	Examples
Absence of specialised personnel like radiologists, sonographers and microscopists. Shortage of healthcare professionals.	Deep learning and machine learning can be used to read and interpret images. Telemedicine facilitates real-time patient monitoring, enabling healthcare providers to detect and address potential health concerns before they are critical. AI-driven symptom checkers and telemedicine platforms provide users with diagnostic insights based on self-reported symptoms and health data (Zawati and Lang, 2024). AI in telemedicine is helping to improve access to health services via chatbots, online platforms and consultations while mitigating some of the risks of self-diagnosis and self-treatment by patients, which can lead to long term complications (Zawati and Lang, 2024).	BabyChecker is being used by non-sonograph experts like community health workers. Zuri Health app allows patients to chat and consult with doctors, buy medication from pharmacies, book labs and diagnostic tests and even have doctor's home visits. Ada Health App helps users to understand the causes of their symptoms and provide medical guidance. Digital-First Integrated Care offers convenient access to qualified doctors and nurses, especially for people living in remote areas. MobiKlinic App equips village community health workers who can enrol patients and connect them to doctors.
Shortage of equipment and laboratory facilities for medical imaging.	Portable digital X-rays and portable ultra sounds systems can be carried to any location.	Ocular uses AI-powered microscopy, by combining smartphones with a 3D printed adapter attachment which can be used into remote areas which are hard to reach.
Lack of reliable internet connectivity and power supply.	AI-driven tools and solutions are offering offline functions (Edge AI).	CAD4TB can operate offline, the CAD4TB Box operates with a rechargeable battery offline. BabyChecker can connect a low cost CE-certified probe to a smartphone and charge the smartphone through solar energy.
Patients travel long distances for medical diagnostics.	Telemedicine e.g. getting support via mobile apps, websites and phone calls is convenient as it reduces the waiting times to see physicians and the cost of travel.	MomConnect is a platform created by the South African Health Department to support pregnant mothers.

Source: ECDPM authors

3.2. Efficiencies in detection and referral

AI is transforming healthcare by significantly improving detection and referral through rapid analyses of large datasets, far beyond human capability. Tools like CAD4TB, a computer-aided detection (CAD) AI-powered software for tuberculosis detection, Ocular an AI-powered microscopy tool and BabyChecker, an AI-powered smartphone-based ultrasound (see section 4) have been specifically designed to enhance both access and efficiency in early detection, enabling quicker confirmatory testing and timely interventions.

One of AI's key advantages is speed. For instance, Ocular AI-powered microscopy detects and classifies parasites and pathogens in real time, significantly reducing malaria diagnostic time by at least 25%. Traditional microscopy can take up to 30 minutes per patient, depending on blood smear quality and technical skill, while Ocular processes images in less than a minute (Wamala, 2025), increasing diagnostic output by 60%. Similarly CAD4TB screens for TB in just 5 seconds (Delft Imaging, n.d.b) allowing for rapid identification and faster referrals.

BabyChecker, with its simple 6-sweep ultrasound scan and intuitive light system, enables non-specialists to detect pregnancy complications quickly and refer high risk cases (red-light indication) to healthcare facilities (Delft Imaging, n.d.a). Moreover, AI-driven point-of-care ultrasound (POCUS) is enabling task shifting from specialised radiology centres to frontline community healthcare workers. In Sierra Leone, community healthcare workers reported that BabyChecker helped them overcome limited ultrasound training, enabling timely identification of high-risk pregnancies and appropriate referrals (Singh, 2024). This task-shifting model demonstrates how AI can extend diagnostic capabilities to lower-level facilities, directly improving patient outcomes through earlier interventions and more efficient use of healthcare resources.

3.3 Improved diagnostic accuracy and enhancing effectiveness

Diagnostic errors refer to inaccuracies or deviations in medical diagnostic procedures that result in overdiagnosis, underdiagnosis or misdiagnosis. AI technologies are playing an important role in addressing these diagnostic challenges by improving accuracy and reducing human error. Tools like Ocular minimise variability among technicians and ensure consistent diagnoses, even in complex cases such as low parasitemia and mixed-species infections, where traditional methods struggle (Nema et al. 2022). Similarly, CAD4TB, endorsed by the WHO, has undergone extensive validation. A 2024 study comparing 5 leading CAD systems in Madagascar, South Africa, Tanzania, Uganda, India, the Philippines and Vietnam found CAD4TB as a top performing AI tool for automated chest X-ray analysis for TB triage (Worodria et al. 2024). The algorithm meets the WHO accuracy benchmarks and enables faster case detection and reduced transmission. This evidence-based validation is key to its adoption in several countries, signifying the importance of scientifically validated AI solutions.

Beyond standalone AI tools, Clinical Decision Support Systems (CDSS) and their diagnostic-focused subset, Diagnostic Decision Support Systems (DDSS) are proving essential in assisting clinicians with diagnosis, management and treatment decisions (Miller 2016). The integration of AI into these systems enhances their effectiveness by enabling rapid, large scale analysis of patient data (Bajwa et al. 2021). AI-powered DDSS have shown particular promise in image-intensive specialties such as radiology and pathology, where they facilitate early detection of diseases like TB and cancer. These systems can identify subtle abnormalities in X-rays, MRI scans and pathology slides that may go unnoticed by human observers, thereby supporting more accurate and timely diagnoses and alleviating pressure on overburdened healthcare systems. The added value of AI is thus in its potential to build health systems by supporting and standardising clinical judgement and applying healthcare processes more objectively with a data-oriented approach (Ciecierski-Holmes et al. 2022).

4. Primer on AI in medical diagnostics: AI use cases

AI has emerged as a revolutionary tool in the medical field especially in medical imaging given the immense data and ability to identify visual patterns which may be imperceptible to the human eye (Kayarian et al. 2024). AI in medical imaging refers to the use of AI, particularly machine learning and deep learning, to analyse medical images such as x-rays, computed tomography (CT scans), and echocardiography (ultrasounds) etc. AI systems assist radiologists and healthcare professionals by enhancing image interpretation, improving diagnostic accuracy, and speeding up the detection of diseases. This section looks at some of the techno-solutions and use cases of AI to improve medical diagnostics specifically in Africa's prevalent diseases of tuberculosis (TB), malaria, and cancer. The section also explores the emerging AI use cases for pre-natal and maternal care, an often overlooked area of healthcare in Africa. These use cases are meant to highlight the value of AI in diagnostics, the value of AI in addressing some of Africa's existing healthcare challenges, and signalling the potential and opportunities that exist in the sector.

4.1 AI in TB diagnosis

Tuberculosis remains a leading infectious killer, with many patients in Africa lacking timely diagnosis and treatment. AI-powered solutions like CAD software from chest x-rays are improving TB screening, particularly in resource-limited regions. In Ghana, minoHealth AI Labs had developed AI systems for screening TB related damage via chest X-Rays (minoHealth AI Labs). It is also used to detect other chest conditions including pneumonia, fibrosis and hernia. It was developed using local data which makes the model suited to Ghana's local context. A benefit of MinoHealth AI is that it has received certification from Ghana's Food and Drug Authority. Similarly in Kenya, Neural Labs has developed NeuralSight, an AI platform that uses deep learning and computer vision to screen medical images from radiologists in real time to identify diseases such as tuberculosis and pneumonia (UNICEF, 2022; Owoko, 2025). In Zimbabwe, local innovator Dr CADx has created an AI image analysis platform that provides doctors with fast and accurate insights when reading X-rays (Africa Com, n.d), which has been trained and tested using local data with radiologists and clinicians.

Aside from African-developed CAD solutions, it is worth mentioning two non-African CAD systems that have been scaled on the continent. CAD4TB, developed in The Netherlands by Delft Imaging Systems in 2005, has since undergone numerous updates. The developers report that it uses deep learning models trained on a diverse dataset across multiple countries, but does not list these countries. However, it has been deployed in over 30 African countries,[6] where local images are captured and used to train in AI upgrades (Interviews 2025). It uses deep learning to analyse chest X-rays rapidly and has been effective in detecting TB among vulnerable populations in South African mines and correctional facilities, as well as through mobile OneStopTB clinics in Malawi (Gondol 2023). In Uganda, CAD4TB is used alongside portable X-ray systems to reach remote areas via the National Tuberculosis and Leprosy Programme (Delft Imaging, n.d.c).

Another example is Qure.ai's system, which uses AI and deep learning to provide automated interpretation of radiology exams like X-rays, CTs and Ultrasounds scans. Founded in 2016 by Indian developers, it aims to enable faster diagnosis and speed to treatment. Its developers claim it is trained on diverse datasets, but provide no list. In South Africa, the KwaZulu-Natal Department of Health in

[6] Benin, Botswana, Burkina Faso, Cameroon, Chad, DR Congo, Eritrea, Eswatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mozambique, Namibia, Niger, Nigeria, Rwanda, São Tomé and Príncipe, Sierra Leone, South Africa, Sudan, Tanzania, Uganda, Zambia, and Zimbabwe.

collaboration with Qure.ai deployed mobile vans equipped with AI-augmented portable X-ray machines in 15 villages across seven provinces, processing over 900,000 scans (Qure ai, 2024). Similarly, collaboration between Qure.ai and Lesotho's Ministry of Health has processed over 6,000 scans since 2022, identifying more than 1,100 potential TB cases, demonstrating AI's role in bridging diagnostic gaps. Although CAD4TB and Qure.ai's AI-driven TB detection systems were developed outside Africa, they have been successfully integrated into African healthcare. Evaluated by the WHO, both systems demonstrated diagnostic accuracy similar to human interpretation of digital chest X-rays in identifying bacteriologically confirmed TB for screening and triage (StopTB, n.d).

Other non-CAD African driven innovations for TB include research by the Kenya Medical Research Institute research to create a mobile phone application which uses AI to diagnose tuberculosis and other respiratory diseases (Africanews, 2024). Its aim is to create software which can accurately recognise a cough connected to TB and other serious diseases. However, software is not yet accurate enough to meet the standard required by the WHO, and has not yet received any regulatory approval, highlighting the importance of validation studies for AI in diagnostics (discussed in section 5.) Nevertheless, this is part of the AI-driven trend of using sound to diagnose illnesses through cough-tracking apps and has been hypothesised as a cheaper tool for screening (Willyard, 2024).

4.2 AI in malaria diagnosis

Malaria remains one of Africa's most prevalent diseases, with the WHO recommending microscopy as the gold standard for diagnosis. To improve accessibility, African innovators are leveraging AI for malaria detection through image analysis (Maturana et al. 2022).

The Makerere AI Health Lab in Uganda, through the Ocular project, is developing AI-driven mobile microscopy for malaria diagnosis. Ocular utilises a 3D-printable adaptor that attaches to a microscope eyepiece, transforming conventional lab tools into AI-enhanced diagnostic systems (Ocular n.d.). Ocular takes advantage of existing technologies such as the smartphone and the availability of at least a microscope in every health centre in Uganda to scale the AI technology across both urban and rural settings. Developed in Uganda using local datasets, the project collaborates with Mulago main referral hospital, which provides images, annotations, and diagnostic validation (Nakasi, 2019). The Ocular project addresses challenges in malaria diagnosis in Uganda, where limited trained laboratory technicians and high patient volumes hinder access to quality diagnostics. AI-powered digital microscopy enables automated parasite detection, parasite level calculations, and faster diagnosis, improving efficiency (Maturana et al. 2022). By transforming traditional microscopes with a 3D-printable adaptor, Ocular expands malaria testing to remote and resource-limited areas, ensuring broader access to high-quality diagnostics.

In Sierra Leone, a study used an AI-based object detection system for malaria diagnosis (AIDMAN study) which employed a deep learning algorithm for detection of Plasmodia in thin-blood-smear images (Liu et al. 2023). The AIDMAN model showed clinically acceptable malaria parasite detection (with a prospective clinical validation accuracy of 98.44% is comparable to that of microscopists).[7] This could aid in malaria diagnosis in resource-limited regions, especially areas lacking experienced parasitologists and equipment.

An interesting non-African innovation on AI in malaria is Noul's miLab™ MAL, a decentralised diagnostic platform which uses AI in point-of-care testing for malaria. The Noul miLab is a fully automated portable digital microscope that prepares a blood film from a droplet of blood, followed by staining and detection of parasites by an algorithm. Infected red blood cells are displayed on the screen of the instrument. Beyond its diagnostic excellence, the device's AI-driven data analytics make it possible to perform real-time monitoring and rapid clinical decisions. This solution eliminates the heavy dependence on specialised personnel and laboratories. Although it is developed by Korean researchers, it is being used by countries in Africa such as Benin, Angola and Cote d'Ivoire as it offers an alternative solution using digital microscopy.

4.3 AI in cancer detection and treatment

AI in cancer detection and diagnosis is another area gaining traction not only globally but also in Africa. Cancer is one of the leading causes of morbidity and mortality worldwide, with approximately 70% of deaths from cancer occurring in LMICs. Cancer causing infections, such as hepatitis and human papilloma virus (HPV), are responsible for up to 25% of cancer cases in LMICs. One of the prevalent cancers on the African continent is cervical cancer which disproportionately affects women in resource-limited settings. The WHO noted that in 2018, 19 of the top 20 countries with the highest cervical cancer burden were in SSA (WHO, 2019).

[7] Clinical validation of AIDMAN was based on 64 patients with thin blood smears at the Sierra Leone-China Friendship Hospital.

Lack of pathology services, infrastructure and specialists is a main challenge leading to lack of access to early diagnosis and treatment. AI technologies are therefore being deployed to address some of these access challenges. For example, DataPathology in Morocco is utilising AI intelligence and image processing technologies to analyse tissue samples and accurately detect signs of cancer (AFDB, 2024). In Uganda, PAPsAI is developing a low-cost digital microscope slide scanner which can produce high resolution cervical cell images to be analysed automatically. Similarly, Ocular which is being used in Uganda for malaria smear microscopy (discussed above) is also being extended to diagnose cervical cancer (Ocular n.d..). AI is also being used in the detection and diagnosis of breast cancer. Strides have been seen in Ghana, where MinoHealth developed an AI system which can diagnose, forecast, and prognosticate conditions like breast cancer and other conditions. In Kenya, Vectogram has developed AI Assisted Mammography Diagnostics (Vectogram, n.d.) These examples are all developed in Africa and use local data sets to train the AI algorithms, which has the benefit of sourcing high-quality, diverse data that accurately represents the target markets and improves the AI performance (Kibuacha, 2024).

4.4 AI for pre-natal and maternal health diagnostics

AI-powered obstetric ultrasound is transforming maternal healthcare by helping detect pregnancy complications, particularly in LMICs, where maternal and perinatal mortality rates remain high. Despite WHO recommendations for routine ultrasounds before 24 weeks of pregnancy, limited access to equipment and trained personnel in LMICs leaves many complications undetected. The lack of antenatal care and lifesaving treatment options exacerbates healthcare inequities, highlighting the urgent need for innovative AI-driven solutions to improve maternal and neonatal outcomes (Shah, 2025).

In Kenya, Google and Jacaranda Health are conducting exploratory research to understand the current approach to ultrasound delivery in the country, and explore how new AI tools could support point-of-care ultrasound for pregnant women (Jacaranda Health, 2024). The project is being piloted among nurses at Jacaranda's sister organisation, Jacaranda Maternity, with the aim of training the AI model to the Kenyan context, and eventually scaling these to be available in lower-access settings, such as rural health clinics. This project provides opportunities to transform maternal healthcare in Kenya by harnessing the power of AI to combat the high rates of maternal and neonatal deaths in the country. Other examples include the AI-based ScanNav FetalCheck software, developed by Intelligent Ultrasound, which is currently being piloted in Uganda (Lay and Okiror, 2024).

One non-African AI technology that is gaining traction in Africa is BabyChecker, a mobile-based AI-powered ultrasound system developed by Delft Imaging, which is used to enhance the detection of high-risk pregnancies. The model has been trained using computer vision and deep learning algorithms applied to ultrasound images from pregnancies across multiple trimesters in diverse settings, including Africa and Latin America (PATH, 2024). BabyChecker employs a six-sweep protocol for obstetric ultrasound analysis, integrating deep learning to assess pregnancy risks effectively.

A key advantage of this technology is its portability and ease of use, enabling community health workers with limited ultrasound expertise to operate it efficiently. Pilot programmes in Sierra Leone have demonstrated its impact, leading to an increase in antenatal care visits and institutional deliveries. This rise in maternal healthcare engagement has also facilitated broader antenatal interventions, such as malaria screenings and tetanus vaccinations (Singh, 2024). In addition to Sierra Leone, BabyChecker has been deployed in Zambia, Kenya and Malawi, further demonstrating its scalability. The technology was also prominently featured at the 2025 Africa Health Agenda International Conference (AHAIC) in Kigali, Rwanda, as a significant innovation for improving maternal healthcare outcomes across the continent (Kahenda, 2025).

5. How to scale AI use cases in diagnostics: policy interventions

For AI to fully transform Africa's healthcare, decisive action should be taken to strengthen AI investments, addressing the barriers to AI development and adoption and creating an enabling environment which attracts innovation while protecting human rights. While AI in diagnostics has enormous potential, it also faces several challenges including infrastructure deficits, data, bias, ethical and regulatory issues, lack of verification and standardisation, and financial costs. Without overcoming these challenges, scaling AI-driven healthcare solutions will be difficult, limiting its impact.

5.1 Financial interventions

a) Costs related to AI development

African governments should **prioritise sustainable investments in developing and scaling strategic AI diagnostic technologies.** Due to high start-up costs and maintenance costs (like software updates or cloud hosting) related to developing and scaling AI diagnostic technologies in Africa, sustainable financing is needed for both the development and scaling of AI technologies. Estimates show that a complex deep learning model for cancer diagnosis and treatment recommendation can start from $50,000 upwards in development costs, while the costs for generative AI are higher as they require specialised expertise in generative techniques and are computationally intensive (Alkhaldi, 2024). Costs for hardware, software, labour (hiring and training), testing, deployment, training of algorithms, and maintenance have to be factored in. Costs related to training the algorithms include data collection and labelling. AI research universities and AI start-ups respectively rely on grant funding and challenge funds but this is seen as unsustainable (Interviews 2025). At present most countries have not been able to meet the AU commitment to allocate 1% of their GDP to promote Africa's R&D and develop innovation strategies for economic development. Nevertheless good examples exist of some countries establishing specific funds or tax relief[8] for companies investing in science, research and innovation, which will benefit AI development. Progress is also being made to fund R&D through Grand Challenges, which are complementary funds that provide an incentive to African governments to increase R&D funding by complementing investments to national innovators, but financial sustainability concerns still remain.

b) Costs in deployment and scaling of AI in diagnostics

African countries **should invest in health economic evaluations which can be used to obtain information about cost-effectiveness**. The cost-effectiveness of scaling AI-powered diagnostic solutions must be carefully assessed, particularly in resource-limited settings where they compete with other primary healthcare needs.[9] AI adoption must demonstrate clear financial and clinical benefits. However, health economic evaluations of AI in healthcare are limited and insights into the actual benefits offered by AI are lagging behind current technological developments (Voets et al. 2022). Studies examining the cost-effectiveness and clinical benefits of AI as a decision-support system, in comparison with traditional diagnostic methods show mixed results depending on the field. For example, while AI has shown promising results in improving outcomes and reducing costs in dermatology and dentistry, its benefits are less clear in ophthalmology (Dorner,

[8] For example in South Africa the R&D Tax incentive is designed to encourage South African companies to invest in scientific or technological research and development activities. It was introduced to help the country achieve a target for R&D expenditure of 1% of GDP.
[9] Full economic evaluations include a cost-effectiveness analysis, cost-utility analysis, cost-benefit analysis and partial evaluations, such as budget impact analysis (see El Arab and Ail Moosa, 2025).

2024). Healthcare organisations must carefully weigh the financial investment against the long-term benefits of improved diagnostic accuracy (Voets et al. 2022). The transition from analogue to digital X-ray technology has notably reduced costs by eliminating consumables like X-ray films. The WHO endorses digital X-rays as a rapid, cost-effective TB screening method prior to confirmatory testing. AI in CAD allows for speedy mass screenings for TB, enabling early identification of TB cases and saving costs from delayed treatment.[10] AI-powered portable ultrasound devices offer a cost-effective alternative to traditional systems by eliminating the need for trained sonographers and allowing midwives and community health workers to operate the technology. These devices improve accessibility and referral efficiency in resource-constrained environments. Ultimately, the cost-effectiveness of AI-enabled diagnostics depends on contextual factors, including financial constraints and healthcare infrastructure.

5.2 Building the African AI stack

AI innovation in health heavily relies on how countries develop AI. African countries should adopt a country-wide approach to AI development where different AI building blocks are developed simultaneously. This involves improvements in internet connectivity, digital skills for AI development, energy efficiency, data regulations, cybersecurity, as well as building of data and AI infrastructures. While countries like South Africa have access to hardware platforms like central processing units and graphic processing units which help with providing fast computational speed and processing capabilities for algorithms (Behara et al. 2022), the majority of African countries lack this computing power, have limited access to raw data and have inadequate supporting infrastructure which is hindering the adoption of AI.

a) Building AI and data center capacities

To drive innovation, African countries must expand data center capabilities, as the continent currently has just over 100 data centers – mainly in South Africa, Nigeria, and Kenya – while estimates suggest at least 700 more are needed to meet connectivity and data storage demands (Carvalho, 2024). African ICT Ministers are also exploring the idea of shared regional data center infrastructure to reduce costs (African ICT Ministerial panel, Paris AI Summit). A study on the state of compute access shows that countries in SSA fall behind major economies such as the US and China (TBI, 2023). Challenges identified include the absence of a

[10] However, evidence on the cost-effectiveness of AI-assisted TB diagnostics, such as CAD4TB, remains mixed. A study in Malawi found no significant cost reductions over an eight-week period, though patient quality of life improved, suggesting the need for long-term economic evaluations.

robust baseline infrastructure and availability of appropriate skills. African countries **should develop strategic partnerships and investments with leading technology companies, to build the necessary infrastructure, train talent and develop next-generation sustainable compute technologies**. As an example, Cassava Technologies announced its plans to build Africa's first AI-enabled data center powered by NVIDIA to accelerate computing which will help African businesses, governments and researchers to access world class AI computing power, enabling them to build, train and deploy AI solutions at scale (Thomas, 2025).

c) Investing in data sets and data annotation for AI in healthcare

Datasets, data annotation and data processing are the core building blocks for AI. However, concerns- sometimes referred to as health data poverty- are that groups who are underrepresented in health datasets are less able to benefit from data-driven innovations developed using such non-inclusive datasets. The lack of quality and diverse datasets is a limitation in training algorithms suitable for African populations, yet an essential component of ensuring algorithmic safety is to guarantee that datasets are appropriately diverse and representative of their intended use population. African countries **should invest in building health data sets locally and regionally.** Examples such as the Lacuna Fund support the creation, expansion, and maintenance of training and evaluation datasets for machine learning and AI, including for healthcare.[11] The Fund supports the development of data sets for malaria in collaboration with Makerere University and Mino Health. Other health data sets include rabies, child malnutrition and brain tumors and diarrhea parasites. When it comes to training AI, strategies like federated learning are being explored to train models locally within clinics, potentially increasing relevance and trust in local contexts (Interviews 2025).

d) Effective integration of AI diagnostics technologies with existing healthcare infrastructures

AI diagnostic technologies **should be integrated into healthcare as essential components of a more efficient system rather than standalone tools.** Effective integration requires interoperability, regulatory alignment, infrastructure investment, training, and continuous evaluation. Integration not only means being able to bring the tool into a health system but also so that the tools are interoperable with existing health information systems. Connectivity of new and existing POCUS diagnostics should be fully integrated with laboratory services to form cohesive diagnostic systems that enhance disease detection. Additionally, AI

[11] Apart from health datasets, the Lacuna Fund supports the development of agriculture, climate and language datasets. More information via https://lacunafund.org/datasets/.

models developed in large hospitals must be adaptable to smaller clinics with diverse patient populations and clinical conditions. Ensuring AI fits within complex clinical workflows is crucial for adoption, with a focus on linking pilot AI in diagnostic projects to national health systems for scalability. Importantly, AI should augment rather than replace human intelligence, maintaining the critical role of human oversight and interaction in medical decision-making while improving efficiency and effectiveness in healthcare delivery (Bajwa et al. 2021).

5.3 Closing regulatory loopholes and developing AI and data regulations

a) Updating data protection and cybersecurity laws

Data protection laws must be **updated to keep pace with technological advancements, ensuring regulatory clarity on health data collection and its secondary uses in AI systems**. While public health and consent are common legal bases for processing health data, clear guidelines are needed to define their scope, particularly in managing large-scale data collection where individual consent is difficult to track. Strengthening a data protection culture is essential, requiring oversight institutions and privacy awareness initiatives. In many cases, hospitals and AI developers share patient data without adhering to legal requirements (Interviews 2025), highlighting the need for stricter compliance. Studies, such as those on Kenya's eHealth applications, reveal that digital platforms often violate local data laws and instead rely on foreign regulations in their privacy notices and privacy policies (Kitili and Karanja, 2023). To address these challenges, awareness programmes should target AI developers handling health data, ensuring adherence to local privacy laws and ethical standards.

Cybersecurity laws need to be updated to avoid data breaches. Medical devices incorporating AI might be exposed to cyberattacks, leading to patient safety and security risks (Biasan, 2024). Ransomware attacks on the African healthcare sector increased by 62% in 2024 (Lemos, 2024).[12] These breaches expose patient data to unauthorised access, and data triangulation can lead to the re-identification of anonymised health records. When patient data is misused outside the doctor-patient relationship, it can negatively impact insurance premiums, employment prospects, personal relationships and even cause social stigma (Mahamadou et al. 2024). To address this, policymakers should take more concrete steps to deal with the growing spectre of cybercrime and misuse of health data.

[12] A 2023 report by African Business showed that approximately 90% of African businesses were operating without cybersecurity protocols in place, making them increasingly vulnerable to cyber threats like hacking, phishing and malware attacks.

b) Developing AI strategies and laws

Digital health laws and digital health strategies should be drafted and / or updated to incorporate the different applications of AI in healthcare. As more African countries develop national AI strategies and data strategies (currently around 16), they should also start looking into AI regulation. The preparatory work may include reviewing how other regions have gone about regulating AI, the focus of their regulatory frameworks and drawing lessons on what might work within African contexts. Regions like the EU have passed AI laws (the EU AI Act) which classify certain AI uses as high risk. For example, AI systems intended for medical purposes need to be subjected to stringent requirements to ensure safety and reliability. Article 10 of the EU AI Act emphasises the importance of data governance for high risk AI systems and mandates data used in training, validation and testing to adhere to strict data management practices. It also prohibits certain AI practices in healthcare such as use of AI solutions that employ subliminal or manipulative techniques to influence patient behaviour, use of AI to exploit vulnerable groups or for social scoring (evaluate individuals based on behaviour or personal characteristics to limit access to healthcare services or adjust health insurance premium).

Aside from regulation, an important element relates to principles for ethical AI which becomes more pertinent when dealing with sensitive data in the health sector. To understand the extent of the problem of algorithmic bias within African healthcare, African researchers should conduct studies on ethical issues on the use of health data within African contexts. What is also needed is for African policy makers to develop AI ethical principles applicable to the health sector making sure that AI algorithms do not reproduce or reinforce existing biases, ensuring privacy, data ownership and benefit sharing. The WHO's guidance on Ethics and Governance for AI in Health and the UNESCO Recommendation on the Ethics of AI can be used as a basis for developing national AI principles which are ethical, responsible, equitable, transparent and reflect local contexts.

c) Strengthening regulatory bodies

To mitigate health risks and safety concerns**, clinically validated AI-powered diagnostic products should be made available on the market**. However, AI-based systems used in healthcare often require approval from regulatory bodies which can be lengthy and complex, as it involves rigorous testing and validation of the AI models. More so, regulatory compliance for AI in healthcare extends beyond a mere initial approval and demands continuous monitoring and reporting to ensure ongoing adherence to standards. This involves regular audits, necessary updates to AI algorithms to guarantee their correct functioning, and the immediate reporting of any adverse events or discrepancies to regulatory bodies. Most African countries lack the capacity for this comprehensive regulatory process which leads to the risk that AI-driven diagnostics are not continuously being monitored which may have adverse health effects.

The **capacity of regulatory bodies to implement standards and certification processes should be strengthened.** At the continental level, AUDA-NEPAD is championing AI integration in health care regulation. It is developing a phased framework to help African regulators gradually adopt AI in healthcare, considering the diverse needs of each nation (AUDA-NEPAD, 2024). This framework offers practical pathways for integrating AI while addressing risks, emphasising ethical oversight, and reinforcing public trust. Key focus includes implementing standardised clinical evaluation and validation protocols that will help regulators maintain consistency in AI diagnostics, thereby building confidence in these solutions among healthcare providers and patients (AUDA-NEPAD, 2024).

Most African countries currently do not have mechanisms to certify AI as a medical device in the healthcare sector. Some examples include MinoHealth's AI technologies that are approved by Ghana's Food and Drug Authority. Lessons can be drawn from the EU's Conformité Européenne (CE) marking which requires product compliance with EU legislation (EC n.d.) or from industry initiatives such as the Radiology Health AI Register which have been developed to increase the transparency of AI in radiography, by providing a list of CE certified software. Similar certifications processes exist in the US through the Food and Drug Authority (FDA) AI-Enabled Medical Devices List which includes a review of the device's overall safety, effectiveness, intended use and technological characteristics.

d) Developing clear data governance frameworks to support innovation

The effective use of health data in AI-driven healthcare depends on responsible data sharing, yet Africa faces challenges due to fragmented governance frameworks. In our previous work, we recommended African countries to develop sector-specific mechanisms on data governance (Musoni et al. 2024). **Ministries of Health should establish clear data governance policies aligned with health laws, digital regulations, and ethical standards to facilitate secure and ethical data sharing with AI researchers while ensuring patient privacy and informed consent.** These frameworks should also address data ownership and equitable profit-sharing in AI-driven health innovations. Proposed approaches include treating AI models trained on publicly funded health data as public goods (Mahamadou et al. 2024), exploring individual compensation and collective data trusts (Olorunju and Adams, 2022), and implementing secure open data initiatives to allow for health data to be shared securely and ethically (Angyiba et al. 2024). Tailoring these strategies to specific country and community contexts will be essential to maximising societal benefits while safeguarding patient rights.

5.4 Strengthening verification and validation processes

Despite the boom in AI for health, verification processes for AI in diagnostics remain weak.[13] **Rigorous validation is essential to ensure that AI-based diagnosis can be used safely and accurately in clinical practice.** Verification and transparency of the effectiveness and efficiency claims of AI in diagnostics in LMIC contexts could increase the trust and their uptake.[14] CAD4TB has undergone numerous independent studies on TB detection in a number of African countries, which has contributed to its wider adoption on the continent. Although AI-driven symptom checkers are seen as potential tools for addressing healthcare challenges, concerns regarding their accuracy and the potential for misdiagnosis persist. Such concerns emphasise the need for rigorous validation, continuous updates and user education to ensure that symptom checkers realise their full potential without compromising patient safety (Wiedermann et al. 2023). Organisations like FIND have developed and implemented the Validation Platform, a system designed to enable independent and reproducible evaluations of CAD software (FIND, n.d). This is aimed at helping vendors evaluate AI-enabled chest X-ray tools for diagnosing TB and other respiratory illnesses, by assessing diagnostic accuracy and consistency across populations (Interviews 2025).

5.5 Empowering health workers through AI skills and capacity building

Both professional and community healthcare workers should be equipped with AI skills*.* Integrating AI into medical curricula will ensure future health professionals can leverage its potential with trust (OECD, 2024). AI-driven educational platforms and decision-support systems can enhance training through interactive modules, simulations and real time feedback. The successful deployment of AI in disease detection and prediction in Africa depends

[13] While reports on the application of different AI technologies in LMICs continue to grow, the actual evidence base has so far not been reviewed. The scope and extent of implemented AI remains unclear, or whether AI technologies have proven to have potential for healthcare delivery in LMICs (Ciecierski-Holmes et al. 2022).

[14] Another important aspect when it comes to AI in diagnostics, is whether their intended use meets the WHO recommended standards for testing for a specific disease (Interviews 2025), to ensure that the proposed AI solutions are helping to solve access challenges to using the appropriate diagnostic method.

significantly on local capacity building and training. Significant investment in education and training programmes especially in remote and rural communities is essential to equip healthcare workers with the skills needed to use AI effectively (Tshimula et al. 2024). A major challenge is the limited availability of AI applications in African local languages,[15] restricting access for many communities. While some developers, such as LugandaGPT and Rwanda's Digital Umuganda, are working to bridge these language gaps through open-source natural language processing tools, further efforts are needed. Initiatives like Ada Health's Swahili version demonstrate the importance of linguistic inclusivity in telemedicine.

6. Strategic steps the EU can take to enhance the scale of AI in diagnostics in Africa

6. 1 The current Europe-Africa partnership on health

Health remains a crucial focus in the partnership between the EU and the AU. The partnership has been developing progressively and currently five Team Europe initiatives (TEIs) have been launched to support this, on: a) manufacturing and access to vaccines, medicines and health technologies in Africa (MAV+) b) digital health, c) One Health d) sexual and reproductive health and e) public health institutions (EU Capacity4Dev). The EU is also committed to the EU–Africa Global Health European and Developing Countries Clinical Trials Partnership (EDCTP3) Joint Undertaking under the Horizon Europe research and innovation funding programme. Public health is also one of the focus areas under the AU-EU Innovation agenda.

Related to diagnostics specifically, following the substantial access challenges to vaccines, diagnostics, medicines and equipment Africa faced during the COVID-19 pandemic, the partnership enhanced support by the EU through sharing of testing kits to several African countries. Team Europe also supported the diagnostic capacity of countries, for example through the EUR 27 million Team Europe backing for Rwanda Biomedical Centre to strengthen pandemic resilience by improving diagnosis, surveillance and research (EIB, 2021).

Several TEIs address aspects relevant to AI in diagnostics such as the TEI digital health, which aims to facilitate the adoption of digital health technologies that will

[15] CAD4TB Platform is available in multiple languages (Arabic, Bahasa Indonesia, Bengali, English, French, Portuguese, Russian, Spanish, Tagalog, Thai, Urdu and Vietnamese). More languages are available upon request.

play a pivotal role in fortifying health security. This will be achieved by providing tools and platforms that enhance preparedness and response to emergencies, as well as improving prevention, diagnosis, treatment, monitoring, and management of health-related issues. Likewise, the TEI MAV+ aims to support manufacturing and access to health technologies which include diagnostics. The EDCTP3 works to deliver new solutions to reduce the burden of infectious diseases in SSA and to strengthen research capacities to prepare and respond to re-emerging infectious diseases globally, including support for diagnostic development.

Additionally, the TEI on Data Governance in Africa could address issues related to governance (at both continental and national level), infrastructure (notably data centres) and data use cases (Musoni et al. 2024), which is crucial when dealing with sensitive health data used in AI developments. The Initiative currently supports digital social innovations (DSIs) through the development of innovative data-driven technology solutions. Two of the current 10 DSIs focus on health; Viya health in Kenya, which is a comprehensive digital platform delivering personalised sexual and reproductive health information and services for women and girls in low and middle income regions; and Macquarie Medical in Namibia, a telemedicine platform designed to improve healthcare accessibility in Namibia, particularly for populations that are geographically and financially isolated (ESTDEV, 2024).

As diagnostic sufficiency remains a key priority for the AU, Africa CDC and African countries, continued support by the EU and other external partners including through innovations such as the use of AI in diagnostics, is important to ensure access to underserved communities. The EU can take several strategic steps to enhance the use of AI in diagnostics in Africa, leveraging its technological and regulatory expertise and fostering equitable partnerships.

6.2 Recommendations to the EU and member states

6.2.1 Funding

Funding remains a significant barrier to both the development and scaling up of AI-driven diagnostics in Africa. The EU can play a crucial role in **incentivising public-private partnerships,** fostering collaborations between European tech firms, African governments, and health organisations. Successful partnerships, such as Babylon Health with Rwanda and Ada Health with South Africa, demonstrate the potential for national-scale AI diagnostic solutions.

Increased investment in research and development (R&D) is also essential, as Africa's limited R&D funding hampers innovation tailored to its specific healthcare needs. Notwithstanding the crucial need for African countries to self-finance R&D programmes, EU **support through multi-year research grants** for African universities and tech hubs could facilitate the development of locally relevant AI models to improve diagnostic accessibility.

The AU-EU innovation agenda, supported by the EU's Global Gateway, prioritises public health and promotes the transformation of research into practical health technologies. The EU should **support collaborations with African research and academic institutions** to develop AI tools suited to local Africa contexts. A good example is the AIMIX (Inclusive Artificial Intelligence for Accessible Medical Imaging Across Resource-Limited Settings) project in Kenya, which will develop a scientific framework for inclusive AI in medical imaging, and demonstrate its relevance for accessible and effective obstetric ultrasound screening in resource-limited rural settings. AIMIX is funded by the European Research Council (ERC) under the EU's Horizon Europe Framework.

Additionally, **better coordination of EU initiatives related to digital health, AI support and data governance is necessary**. The Directorate-General for Health and Food Safety's AICare@EU framework is already examining AI deployment in healthcare, and a dedicated working group could help align funding and programming efforts to expand AI-powered diagnostic access, particularly for underserved populations.

6.2.2 Infrastructure

Infrastructure challenges hinder the large-scale deployment of AI in diagnostics across Africa. While the EU's Global Gateway initiative aims to scale up investment in digital infrastructure (Teevan and Domingo, 2022), **further efforts are needed to expand broadband and cloud computing services to support AI-powered healthcare**. Given connectivity limitations, AI developers targeting low- and middle-income countries are leveraging Edge AI, which processes data locally on devices rather than relying on centralised cloud systems. This enables real-time decision-making, reduces server load and enhances scalability. Edge AI applications in medical imaging, such as CAD4TB and BabyChecker, allow offline deployment, facilitating faster diagnoses in remote areas. Team Europe can support both Edge AI and cloud-based diagnostic technologies. Additionally, interoperability remains a challenge in integrating AI diagnostics within existing health systems and across public and private providers. The EU's expertise in managing interoperability within the Electronic Health Record (EHR) system presents an opportunity to share experiences with African countries in developing similar frameworks for seamless healthcare integration.

6.2.3 AI in health regulations and ethical guidelines

The EU has pioneered AI regulation with the AI Act and the establishment of an AI Office to ensure compliance. The EU also unveiled its International Digital Strategy aimed at enhancing European competitiveness through economic and business cooperation, whilst seeking to shape itself as a 'reliable partner' on global digital governance and standards. As a strategic partner, Team Europe is supporting African countries in strengthening regulatory capacities through initiatives like the EU Action on Data Governance in SSA. For AI in diagnostics, knowledge sharing on the provisions of the EU AI Act for high-risk applications, such as AI-driven medical software, can inspire African countries in developing safety, transparency, and ethical standards. Additionally, the European Health Data Space (EHDS) regulation provides a framework for the ethical and secure secondary use of health data in AI innovation. Sharing EU expertise in AI governance and ethical data use will support African countries in advancing AI-driven healthcare while **ensuring compliance with data protection and ethical principles**. The D4D Hub's AI Working Group could facilitate engagement between the EU AI Office, African partners, and key EU institutions to share lessons on AI regulation, digital health laws, and cross-ministerial coordination.

6.2.4 Certification processes

The EU should use the lessons from the EU's AI Act and the EU CE marking for harmonisation legislation to **support capacity building of African regulators to develop similar certification processes** on ensuring the safety of AI in health (diagnostics) that is used on the continent. For example, Article 48 of the EU AI Act requires that for high-risk AI systems embedded in a product, a physical CE marking should be affixed, and may be complemented by a digital CE marking, whereas for high-risk AI systems only provided digitally, a digital CE marking should be used. At present, Africa lacks continental wide regulations on certifications for AI systems in health. Collaboration with AUDA-NEPAD, AMDF, AFCAD could help develop continental protocols that will help regulators regulate and implement conformity assessments in AI in diagnostics.

6.2.5 Verification of AI in diagnostics

Verification and validation of the effectiveness of AI diagnostics remains limited, particularly in African contexts. The EU's SHAIPED project offers opportunities for collaboration by facilitating knowledge exchange on how to validate the clinical effectiveness of AI-based medical devices at a broader scale, ensuring they meet standards and are effective for patient care. Through initiatives like Horizon Europe and the upcoming FP10, the EU **should fund research and innovation**, including grants for clinical validation of AI diagnostics in SSA, ensuring alignment with local disease profiles such as malaria and tuberculosis and NTDs. Economic incentives and regulatory measures may be necessary to encourage developers to validate AI solutions using locally relevant data. Establishing regulatory sandboxes in partnership with the AU, Africa CDC, AFCAD, AUDA-NEPAD and WHO would enable controlled testing of AI diagnostics before scaling, ensuring compliance with WHO standards for disease screening, detection, and diagnosis. Opportunities lie in supporting regional data sharing for AI training and establishing a Pan-African AI regulatory sandbox.

6.2.6 Capacity

The effective use of AI technologies in healthcare requires adequate training for both professional and community healthcare workers, as well as the general population, particularly with the rise of AI-powered symptom checker apps. Education and training should be integrated into formal curricula and community programmes, with a focus on language accessibility. The EU should **support AI education and capacity-building efforts** tailored to Africa's local contexts to enhance accessibility and adoption.

7. Conclusion

Diagnostic sufficiency is a priority in Africa due to the continent's high disease burden, necessitating robust diagnostic tools for early detection and treatment. While there is significant political interest in scaling up AI-driven diagnostics, such initiatives must account for Africa's AI ethics, policies and regulatory landscape. Global health disparities often impact AI deployment in Africa, underscoring the importance of locally trained AI models that minimise ethical biases and consider the continent's diverse socio-economic conditions.

The AU has introduced policy frameworks, such as the AU Continental AI Strategy, the Data Policy Framework, the Digital Transformation Strategy and the Africa

CDC's Digital Transformation Strategy to guide AI adoption in healthcare. However, Africa lacks a dedicated AI legal framework, and no country has enacted sui generis AI laws. The absence of regulatory safeguards presents risks, particularly concerning ethical guidelines, security and privacy protections for sensitive health data. AI as a medical device introduces distinct regulatory challenges that must be addressed to ensure safe implementation.

African AI researchers and innovators are increasingly developing AI solutions to address healthcare challenges. AI presents an opportunity to enhance equitable healthcare access, but its effectiveness depends on suitable infrastructure, skilled personnel, sustainable funding and solutions tailored to local contexts. In this paper, AI-driven diagnostic use cases have shown success in improving efficiency, accuracy and accessibility, particularly for tuberculosis, malaria, cancer, prenatal, and maternal care. Locally trained AI models have proven effective, and even non-African-developed solutions have been successfully integrated into African settings through validation processes. Offline deployment options, such as CAD4TB Box and BabyChecker, enhance AI's applicability in rural areas with limited internet and electricity access.

Despite these advantages, several challenges hinder the widespread adoption of AI diagnostics. Financial constraints, integration with existing healthcare infrastructure and regulatory inconsistencies pose significant barriers. Data governance frameworks must balance patient privacy with the need for AI training data, and verification processes are essential to build public trust and ensure safe clinical implementation. Strengthening AI regulations and cybersecurity measures is critical to protecting sensitive health data, while healthcare professionals must be adequately trained to utilise AI technologies effectively.

As a key partner, the EU can play a pivotal role in scaling AI diagnostics in Africa. Public-private partnerships, as seen in Rwanda and South Africa, and EU-supported digital infrastructure and data projects under the Global Gateway initiative can facilitate AI development. Knowledge-sharing between the EU and African nations on AI regulation and ethics will further support the adoption and scaling up of AI in healthcare. Establishing a working group to coordinate EU initiatives in AI for health broadly as well as specific diagnostics, could enhance sustainable implementation efforts. Finally, as a number of AI in healthcare are being piloted and scaled on the African continent, these provide avenues for mutually beneficial collaboration between the EU and Africa as these AI solutions could be replicated to benefit European health systems. For example, through the use of CAD4TB for screening for TB.

References

AfDB (2024). DataPathology: combining artificial intelligence and digital technology to combat cervical cancer. (Accessed 13 September 2025).

Africa Centres for Disease Control and Prevention (2023). Africa CDC Digital Transformation Strategy Edition 2023.

Africa Com (2024). Hot startup of the month: Zimbabwe's Dr CADx. (Accessed 13 September 2025).

Africanews (2024). Kenyan scientists test AI app to diagnose tuberculosis. (Accessed 15 September 2025).

African Union (2018). Africa Centres for Disease Control and Prevention and partners launch the Africa Collaborative Initiative to Advance Diagnostics - AFCAD to address existing barriers towards advancing the diagnostic agenda in Africa.

African Union Commission (2014). African Union Convention on Cyber Security and Personal Data Protection.

African Union Commission (2020). The Digital Transformation Strategy for Africa 2020–2030.

African Union Commission (2023). AU Data Policy Framework.

African Union Commission (2023). Digital transformation strategy - Empowering people, strengthening health systems.

African Union Commission (2024). Continental Artificial Intelligence Strategy: Harnessing AI for Africa's Development and Prosperity.

Ahmat, A. et al. (2022). The health workforce status in the WHO African Region: findings of a cross-sectional study. BMJ Glob Health. 7 (Suppl 1).

Alkhaldi, N. (2025). Assessing the cost of implementing AI in healthcare. Warsaw: Itrex.

Angyiba, S.A., Ngnotouom Ngnokam, T.C., Mafo Kamga, L.D. and Ewane, E. (2024). Transforming African Healthcare with AI: Paving the Way for Improved Health Outcomes. Journal of Collaborative Healthcare and Translational Medicine. https://doi.org/10.47739/2333-7125/1046.

AUDA-NEPAD (2024). AUDA-NEPAD Champions AI Integration in Healthcare Regulation at 4th African Medicines Regulatory Harmonisation Week. (Accessed 12 September 2025).

AUDA-NEPAD (n.d.). Africa Medical Devices Forum (Accessed 15 September 2025).

AUDA-NEPAD and APET (2024). AUDA-NEPAD White Paper: Regulation and responsible adoption of AI in Africa towards achievement of AU Agenda 2063.

Bajwa, J., Munir, U., Nori, A. and Williams, B. (2021). Artificial intelligence in healthcare: transforming the practice of medicine. Future Healthcare Journal. https://doi.org/10.7861/fhj.2021-0095.

Behara, K., Bhero, E., Agee, J.T. and Gonela, V. (2022). Artificial intelligence in medical diagnostics: A review from a South African context. In: Scientific African, volume 17.

Biasin, E., Kamenjašević, E. and Ludvigsen, K.R. (2024). 4: Cybersecurity of AI medical devices: risks, legislation, and challenges. In: Research Handbook on Health, AI and the Law.. https://doi.org/10.4337/9781802205657.ch04

Carvalho, S. (2024). Data centers - Just one part of the African digital infrastructure investment equation. Data Center Dynamics.

Ciecierski-Holmes, T., Singh, R., Axt, M., Brenner, S. and Barteit, S. (2022). Artificial intelligence for strengthening healthcare systems in low- and middle-income countries: A systematic scoping review. Digital Medicine, 5, Article 162.

Delft Imaging (n.d.a). BabyChecker: Artificial Intelligence for Safer Pregnancies.

Delft Imaging (n.d.b) Computer-Aided Detection for Tuberculosis.

Delft Imaging (n.d.c.). Delft supports Uganda’s combat against TB.

Dominic, C. (2025). AI Laws: A Global Overview with a Focus on Africa. Tech Culture Africa.

Dorner, C. (2024). Evaluating the Role of Artificial Intelligence in Healthcare: Costs and Clinical Benefits. LinkedIn. (Accessed 15 September 2025).
EIT Health (2024). SHAIPED and the European Health Data Space (EHDS): Shaping the Future of AI-Driven Healthcare in Europe. (Accessed 13 September 2025).

El Arab, R.A. and Al Moosa, O.A. (2025). Systematic review of cost effectiveness and budget impact of artificial intelligence in healthcare. NPJ Dicital Medicine.

Ephraim et al. (2024). Application of medical artificial intelligence technology in sub-Saharan Africa: Prospects for medical laboratories. In: Journal of Global

Fleming, K.A. et al. (2021). The Lancet Commission on diagnostics: transforming access to diagnostics. Lancet. doi: 10.1016/S0140-6736(21)00673-5.

Health Reports, 8. https://doi.org/10.1016/j.smhl.2024.100505.

ESTDEV (2024). Empowering African innovation: Estonia and partners support digital-social innovation in Africa. (Accessed 12 September 2025).

EU Artificial Intelligence Act (n.d.). Article 48: CE Marking.

European Commission (n.d.a). CE marking. (Accessed 15 September 2025).

European Commission (n.d.b). Artificial Intelligence in healthcare. (Accessed 12 September 2025).

European Commission (2025). Joint Communication on an International Digital Strategy for the EU.

European Investment Bank (2021). Rwanda: EUR 27 million Team Europe backing for Rwanda Biomedical Centre to strengthen pandemic resilience. (Accessed 14 September 2025).

European Union (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 aying down harmonised rules on artificial intelligence and amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU)

2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act).

FIND (n.d.). Validation Platform for AI-based diagnostic evaluation. (Accessed 14 September 2025).
Global Gateway (2023). The AU-EU Innovation Agenda.

Guo, A. and Morio, M. (2024). Artificial intelligence as a medical device regulatory landscape - Current state, key challenges, and guidance for partners. PATH.

Jacaranda Health (2024). The BBC highlight Jacaranda's partnered project around AI-assisted ultrasound. (Accessed 15 September 2025).

Kahenda, M. (2025). Africa adopts AI technology in healthcare to boost diagnosis. The Standard. (Accessed 14 September 2025).

Kariuki. S., Kering, K., Wairimu, C., Onsare, R. and Mbae, C. (2022). Antimicrobial resistance rates and surveillance in sub-Saharan Africa: Where are we now? Infectious Diseases and Therapy, 15, 3589–3609.

Kayarian, F BS. et al. (2024). Artificial intelligence and point-of-care ultrasound: Benefits, limitations, and implications for the future. In: The American Journal of Emergency Medicine. Volume 80. Pages 119-122. https://doi.org/10.1016/j.ajem.2024.03.023.

Kibuacha, F. (2024). Closing the Gap: How Local Context Improves AI Performance in Emerging Regions. Denver: GeoPoll.

Kiseleva, A., Kotzinos, D., and De Hert, P. (2022). Transparency of AI in healthcare as a multilayered system of accountabilities: Between legal requirements and technical limitations. Frontiers in Artificial Intelligence, 5, Article 879603. https://doi.org/10.3389/frai.2022.879603.

Kitili, J. and Karanja, N. (2023). The New Wave of eHealth: AI and Privacy Concerns? A Case Study of Kenya. Strathmore University.

Komminoth, L. (2023). Africa's cybersecurity threat. African Business.

Lay, K. and Okiror, S. (2024). 'I am happy to see how my baby is bouncing': the AI transforming pregnancy scans in Africa. The Guardian.

Lemos, R. (2024). South Africa National Healthcare Lab Still Reeling From Ransomware Attack. Dark reading. (Accessed 15 September 2025).

Liu, R., Liu, T., Dan, T., Yang, S., Li, Y., Luo, B., Zhuang, Y., Fan, X., Zhang, X., Cai, H. and Teng, Y. (2023). AIDMAN: An AI-based object detection system for malaria diagnosis from smartphone thin-blood-smear images. https://doi.org/10.1016/j.patter.2023.100806

Mahamdou, A.J., Ochasi, A. and Altman, R.B. (2024). Data Ethics in the Era of Healthcare Artificial Intelligence in Africa: An Ubuntu Philosophy Perspective. https://doi.org/10.48550/arXiv.2406.10121.

Mateen, B. (2024). Can AI improve health care delivery in Africa? 5 things you should know. PATH.
Maturana, C.R. et al. (2022). Advances and challenges in automated malaria diagnosis using digital microscopy imaging with artificial intelligence tools: A review. Sec. Infectious Agents and Disease. Volume 13 - 2022. https://doi.org/10.3389/fmicb.2022.1006659

Miller, R.A. (2016). Diagnostic Decision Support Systems. In: Berner, E. (eds) Clinical Decision Support Systems. Health Informatics. Springer, Cham. https://doi.org/10.1007/978-3-319-31913-1_11.

minoHealth AI Labs (n.d.). Democratizing quality healthcare: Artificial intelligence powered solutions.

Musoni, M., Karkare, P., and Teevan, C (2024). Cross-border data flows in Africa: Continental ambitions and political realities. Maastricht: ECDPM.

Nakasi, R. (2019). Ocular Project —Simplyifying Micrscopy Diagnosis through Artificial Intelligence. AI Research.

Nam, J.M. (2023). Noul to export $1.4 mn in malaria diagnostic kits to Angola. The Korea Economic Daily. (Accessed 14 September 2025).

NCAIR and NITDA (2024). National Artificial Intelligence Strategy 2024. National Centre for Artificial Intelligence and Robotics.

Nema, S., Rahi, M., Sharma, A. and Bharti, P.K. (2022). Strengthening malaria microscopy using artificial intelligence-based approaches in India. Lancet Regional Health – Southeast Asia. https://doi.org/10.1016/j.lansea.2022.100054

Nsoesie, E.O. (2024). Using AI to Decolonize Health Care in Africa. Think Global Health.

Ocular (n.d.). Ocular Uganda. (Accessed 14 September 2025).

OECD (2024). Artificial Intelligence and the health workforce - Perspectives from medical associations on AI in health.

Olorunju, N. and Adams, R. (2022). African data trusts: New tools towards collective data governance? Research ICT Africa.

Owoko, L. (2025). How AI is transforming Kenya's medical imaging. Business Daily Africa.

PATH (2024). Public Health Impact through AI (PhixAi) Innovation Compendium 2024.

PATH (2025). Accelerating the Effective and Ethical Use of Large Language Models in Primary Health Care Settings in Sub-Saharan Africa.

Postelnicu, L. (2020). Babylon inks 10-year partnership with Rwandan government. Mobi Health News.

Qure.ai and THINK (2024). Leveraging AI for tuberculosis diagnosis in South Africa.

Republic of South Africa (2020). National Digital Health Strategy for South Africa 2019–2024. Pretoria: National Department of Health.

Sekati, P. (2025). AI bias in sexual and reproductive health in Africa. ALT Advisory.

Shah, S. (2025). Navigating Diagnostic Deserts: How Portable Ultrasound is Improving Maternal Healthcare in Africa. MedCityNews.

Singh, K. (2024). BabyChecker: Bridging the gap in maternal care, one scan at a time. New Security Beat.

Stop TB Partnership (n.d.). Screening and Triage for TB using Computer-Aided Detection (CAD) Technology and Ultra-Portable X-Ray Systems: A Practical Guide.

Teevan, C. and Domingo, E. (2022). The Global Gateway and the EU as a digital actor in Africa. Discussion paper 332. Maastricht: ECDPM.

Thomas, D. (2025). Cassava and Nvidia to launch Africa's 'first AI factory'. African Business. (Accessed 14 September 2025).
Tony Blair Institute for Global Change (2023). State of Compute Access: How to Bridge the New Digital Divide. (Accessed 15 September 2025).

Townsend, B.A., Sihlahla, I., Naidoo, M., Naidoo, S., Donnelly, D.-L., and Thaldar, D.W. (2023). Mapping the regulatory landscape of AI in healthcare in Africa. Frontiers in Pharmacology, 14, Article 1214422.

Transform Health Coalition (2025). Digital-First Integrated Care : Rwanda's innovative digital healthcare service.

Tshimula, J.M. et al. (2024). Artificial Intelligence for Public Health Surveillance in Africa: Applications and Opportunities. Cornell University. https://doi.org/10.48550/arXiv.2408.02575

UNESCO (2024). Recommendation on the Ethics of Artificial Intelligence.

UNICEF (2022). Neural Labs: Using AI to accelerate medical imaging diagnosis for respiratory diseases. Venture Fund.

Varnosfaderani, S.M. and Forouzanfar, M. (2024). The role of AI in hospitals and clinics: Transforming healthcare in the 21st century. Bioengineering, 11(4), 337.

Vectorgram (n.d.). Reimagining Breast Cancer Screening using AI.

Victor, A. (2025). Artificial intelligence in global health: An unfair future for health in Sub-Saharan Africa? .https://doi.org/10.1093/haschl/qxaf023.

Voets, M.M., Veltman,. J., Slump, C.H., Siesling, S. and Koffijberg, H. (2022). Systematic Review of Health Economic Evaluations Focused on Artificial Intelligence in Healthcare: The Tortoise and the Cheetah. https://doi.org/10.1016/j.jval.2021.11.1362

Wamala, D. (2025). How AI is rewriting future of diagnostics. Daily Monitor.

Wiedermann, C.J., Mahlknecht, A., Piccoliori, G. and Engl, A. (2023). Redesigning Primary Care: The Emergence of Artificial-Intelligence-Driven Symptom Diagnostic Tools. J Pers Med. 10.3390/jpm13091379.

Willyard, C. (2024). These AI-powered apps can hear the cause of a cough. (Accessed 14 September 2025).
World Health Organization (2019). Cervical cancer. (Accessed 15 September 2025).

World Health Organization (2021). Generating Evidence for Artificial Intelligence-Based Medical Devices: A Framework for Training, Validation, and Evaluation.

World Health Organization (2023). Regional strategy on diagnostic and laboratory services and systems 2023–2032 for the WHO African Region.

World Health Organization (2024). Ethics and governance of artificial intelligence for health - Guidance on large multi-modal models.

Worodria, W., Castro, R., Kik, S.V., Dalay, V., Derendinger, B., Festo, C., Nguyen, T.Q., Raberahona, M., Sudarsan, S., Andama, A., Thangakunam, B., Lyimo, I., Nguyen, V.N., Rakotoarivelo, R., Theron, G., Yu, C., Denkinger, C.M., Lapierre, S.G., Cattamanchi, A., Christopher, D.J., and Jaganath, D.; R2D2 TB Network (2024). An independent, multi-country head-to-head accuracy comparison of automated chest x-ray algorithms for the triage of pulmonary tuberculosis. medRxiv. https://doi.org/10.1101/2024.06.19.24309061

Zawati, M-H. and Lang, M. (2023). Does an app a day keep the doctor away? AI symptom checker apps, regulation, transparency, and health equity. Journal of Law and the Biosciences, 10(1), lsad006.

About ECDPM

ECDPM is an independent 'think and do tank' working on international cooperation and development policy.

Since 1986 our staff members provide research and analysis, advice and practical support to policymakers and practitioners across Europe and Africa – to make policies work for sustainable and inclusive global development.

Our main areas of work include:

- EU foreign and development policy
- Migration and mobility
- Digital economy and governance
- AU-EU relations
- Peace, security and resilience
- Democratic governance
- Economic recovery and transformation
- Climate change and green transition
- African economic integration
- Sustainable food systems

For more information please visit www.ecdpm.org

This document has been produced with the financial assistance of the European Union. The contents of this document are the sole responsibility of the authors and can under no circumstances be regarded as reflecting the position of the European Union. This publication also benefits from the structural support by ECDPM's institutional partners: The Netherland, Austria, Belgium, Denmark, Estonia, Finland, Ireland, Luxembourg and Sweden.

ISSN1571-7577

ecdpm

HEAD OFFICE
SIÈGE
Onze Lieve Vrouweplein 21
6211 HE Maastricht
The Netherlands *Pays Bas*
Tel +31 (0)433 502 900

BRUSSELS OFFICE
BUREAU DE BRUXELLES
Avenue des Arts 44, 1040
Brussels *Bruxelles*
Belgium *Belgique*
Tel +32 (0)2 882 50 08

info@ecdpm.org
www.ecdpm.org
KvK 41077447