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Application of medical artificial intelligence technology in sub-Saharan Africa: Prospects for medical laboratories

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ABSTRACT

The widespread adoption of artificial intelligence (AI) technology globally has brought significant changes to various sectors. AI-assisted algorithms have notably improved decision-making, operational efficiency, and productivity, especially in healthcare and medicine. However, in low and middle-income countries (LMICs), particularly in sub-Saharan Africa (SSA), the integration of medical AI has faced delays and challenges, slowing its acceptance and implementation in medical interventions. This thematic narrative critically explores the current trends and patterns in applying medical AI in SSA, with a specific focus on its potential impact on medical laboratories. The review covers the general use of medical AI in SSA, examining factors like enablers, challenges, and opportunities that influence healthcare systems. Additionally, it looks into the implications of medical AI for medical laboratories and suggests context-specific and practical recommendations for potential integration. We highlight various challenges, including data availability, security concerns, resource limitations, regulatory gaps, poor internet connectivity, and digital literacy issues, contributing to the slow integration of AI in healthcare systems in SSA. Despite challenges, the adoption of medical AI in SSA medical laboratories holds latent potential for improving diagnostic accuracy, streamlining workflows, and enhancing patient care. Further exploration and careful consideration are necessary to unlock these possibilities.

1. Introduction

Globally, the medical laboratory space has evolved since the 1950s, mainly shifting from manual laboratory testing to automation (Thurow, 2023). The introduction of automated diagnostics in clinical laboratory settings has generally decreased the workload and human errors of medical laboratory professionals. Notwithstanding its success, manual methods are very technical and laborious and often lead to human errors in the analytical process (Alaidarous, 2020). Given that an accurate diagnosis is the cornerstone of effective disease management and more than 70% of medical decisions are based on laboratory results (Badrick, 2013; Sikaris, 2017), automation has decreased turnaround time and improved reproducibility, test quality, and efficiency (Cherkaoui et al., 2020). Although there is heterogeneity among trained medical laboratory professionals, automation has standardized and harmonized laboratory

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diagnostics (Lippi & Da Rin, 2019). Medical laboratory professionals can now perform more complex tests while ensuring the quality of test results and troubleshooting analyzers to maintain quality test outcomes.

With continued global technological advancements, artificial intelligence (AI) is revolutionizing and enabling businesses and institutions in education (Chen et al., 2020), manufacturing (Plathottam et al., 2023), wastewater treatment (Wang et al., 2023), the creative space (Anantrasirichai & Bull, 2022), and healthcare (Bajwa et al., 2021; Davenport & Kalakota, 2019), among others. Sub-Saharan Africa (SSA) has seen notable AI applications across various sectors. In 2007, the revolutionary digital payment platform M-Pesa was launched in Kenya, later integrating AI algorithms for enhanced services (Vodafone, 2019). South Africa's JUMO, an intelligent banking technology, emerged in the 2010s (JUMO, 2024). In healthcare, Zimbabwe's Dr. CADx, which aids radiologists with diagnostics, appeared in the mid-2010s (Dr CADx, 2022). Around the same period in 2014, South Africa's Aerobotics (Aerobotics, 2024) and Nigeria's Hello Tractor (Atlas AI, 2024) improved farming mechanization and efficiency. AI-powered educational platforms like Kenya's M-Shule, which educates hard-to-reach populations (M-Shule, 2024) and Nigeria's Ubenwa, which monitors and interprets infant cries (Ubenwa, 2024), have also gained traction. More recently, Ghana's GridWatch (CEGA, 2024) and WaterScope in South Africa, Ethiopia and Tanzania (WaterScope, 2020) have improved infrastructure monitoring through AI-powered crowdsourced information on power grid reliability and water quality testing, respectively. The vast field of AI has achieved significant traction in medicine and healthcare in general, using varying methods and algorithms in diagnostics, simulations, large data analysis, and machine learning. The historical context of AI in medicine and healthcare dates back to the 1950s, with pioneers exploring its potential (Russell et al., 2016). In the 1960s and 1970s, rule-based expert systems for diagnosis and decision support emerged (Shortliffe & Buchanan, 1975). However, progress was limited by computational constraints. By the 1980s, advances in machine learning laid the foundation for more sophisticated AI algorithms (Mitchell, 1997). The proliferation of electronic health records (EHRs) in the 2000s enabled the collection of large datasets, fueling the development of AI-driven diagnostic tools and predictive analytics (Davenport, 2019). Recent breakthroughs in deep learning and natural language processing have transformed medical imaging, drug discovery, personalized medicine, and patient care (Topol & Verghese, 2019), with ongoing efforts to address challenges related to data privacy, regulation, and ethics. Owing to the success in developed countries, it is therefore imminent that discussions be held about introducing and leveraging AI in laboratory diagnosis, particularly in countries with limited resources. AI systems have the capability of revolutionizing laboratory procedures by using sophisticated analytical tools, boosting diagnostic accuracy, and reducing workflow (Paranjape et al., 2021). The integration of AI in the medical laboratory would represent a significant breakthrough toward enhancing diagnosis and overall patient outcomes.

Resource-limited settings such as SSA are challenged with a disproportionately high burden of infectious diseases, including malaria, HIV, cholera, meningitis, and tuberculosis, among others. In addition, regulatory entities remain fragmented, further complicating implementation in SSA. These unique challenges are met with limited access to healthcare infrastructure funding and advanced diagnostic technologies and a shortage of skilled healthcare professionals (Amu et al., 2022; Moyo et al., 2023). With these limitations, integrating AI into medical laboratories holds enormous promise for improving diagnostic capabilities and patient care and addressing long-standing healthcare disparities. This review profiled the current application of medical AI and the challenges that impede its implementation in SSA. The available opportunities for integrating medical AI to improve healthcare systems in the SSA are also discussed. Ultimately, this review demonstrates the implications of Medical AI in medical laboratory practice in SSA.

2. Methods

2.1. Review framework

This review's methodological foundation was built on the framework by Arksey and O'Malley (Arksey & O'Malley, 2005). The evidence synthesis stages included the identification of the research question, data search, data screening and selection of eligible articles, data charting, and reporting. The research question was: "What are the current applications of Medical AI in SSA?".

2.2. Data search and screening

The data search and screening process adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analysis approach (Peters et al., 2015). A comprehensive search of relevant electronic databases including Scopus, PubMed, EBSCOHost, Web of Science, and CINAHL was conducted using identified keywords and index search terms relevant to the research question. An additional search was conducted through citation matching and web search. The following search terms and relevant keywords were used in different combinations with Boolean operators (AND, OR) in the search process: application, use, medical AI, medical artificial intelligence, healthcare, diagnosis, machine learning, deep learning, sub-Saharan Africa, SSA, challenges, prospects, and opportunities. For example, (artificial intelligence or ai or a.i.) AND (healthcare or medical care or medicine or health care) AND (sub saharan africa or

Table 1
Population, Concept, and Context (PCC) framework for the study.

Population	All populations
Concept	Medical AI applications
Context	Sub-Saharan Africa (SSA)

sub-saharan africa or sub sahara or sub-sahara or ssa). The search query encompassed data spanning all years up to 2023. The Population, Concept, and Context (PCC) framework was employed to guide the eligibility of the individual studies included in the review (Table 1) (Aromataris & Munn, 2020). The study included research conducted in SSA, focusing on the use of Medical AI in the region. Additionally, only studies published in English were considered. However, grey and review articles were excluded. Studies were exported to the Rayyan review manager for thorough screening and selection (Rayyan, 2022). A three-phase screening by two (2) independent reviewers was employed (screening by titles, abstracts, and full texts). An additional reviewer was employed to resolve review conflicts. The findings of the evidence synthesis were presented in the narrative format while profiling emerging themes, trends, and patterns in the application of medical AI in SSA and its prospects in medical laboratory practice. The results focused on different aspects, such as how medical AI is used in the SSA region, what challenges its implementation, opportunities for improving healthcare, the effects of medical AI on medical laboratories, and suggestions for its application in SSA's medical laboratories.

2.2.1. *Data search output*

A total of 654 articles extracted from Scopus (n = 22), CINAHL (n = 81), PubMed (n = 126), EBSCOHost (n = 420), and additional 5 articles identified by citation and web search were initially screened for duplicates (Fig. 1). The reviewers identified and removed 350 duplicates and subsequently screened the titles of 304 articles. At this screening phase, 12 articles failed to meet inclusion criteria, and 292 articles were screened by abstract. Here, 24 articles were excluded, and 268 articles met inclusion criteria for full-text screening. Full-text screening led to the exclusion of 244 articles. The reviewers excluded articles that were not conducted in SSA, review articles, and articles that did not focus on the application of medical AI (Fig. 1). Full-text screening produced 24 articles that met inclusion criteria (Table 2).

2.2.2. *Quality appraisal*

The 24 included articles were appraised to assess the quality of their methodology using the Excel spreadsheet of the Mixed Methods Appraisal Tool (MMAT) version 2018 (Hong et al., 2018). Absolute quality scores were calculated and classified according to the level of quality of evidence as follows: weak (≤50%), moderately weak (51–65%), moderately strong (66–79%), or strong (80–100%) (Li et al., 2015). One study had weak quality of evidence (Glaser et al., 2023). Four studies had moderately weak quality

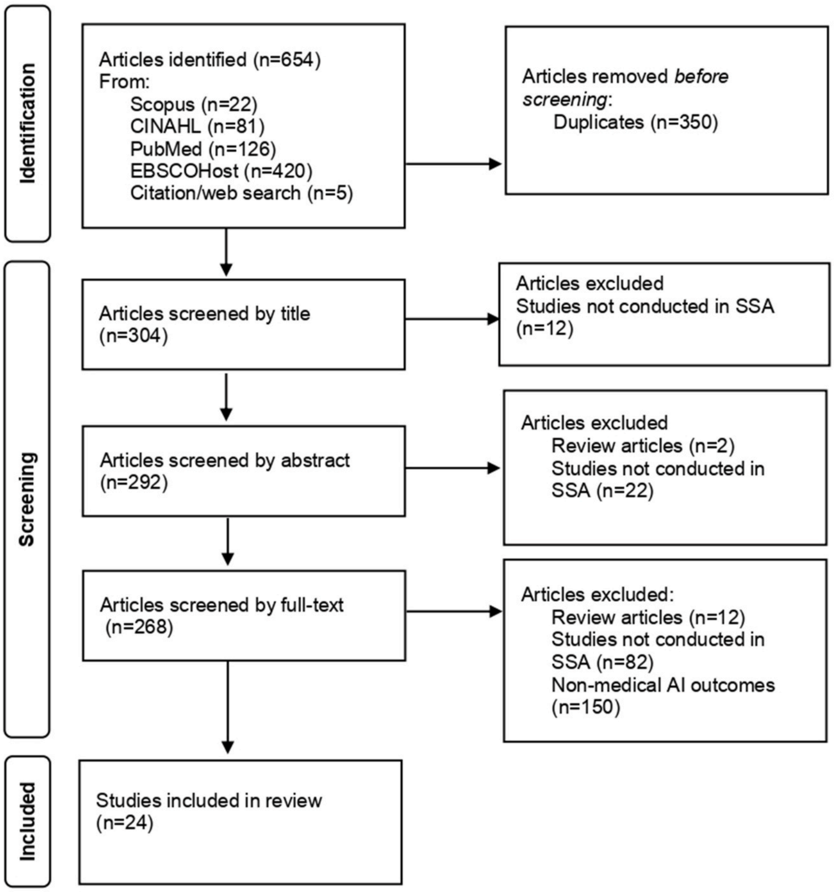

Fig. 1. Screening for eligible studies.

Table 2
The characteristics of eligible studies.

Author/Year	Country	Study design	Sample size/ number of patients	Study duration	Specialty	Disease	AI algorithm/model
Glaser et al. (2023)	Lesotho and South Africa	Case series	4 patients	–	Medical Imaging	Tuberculosis	Computer-aided detection (CAD) software
Sendra-Balcells et al. (2023)	Egypt, Algeria, Uganda, Ghana and Malawi	Model evaluation	25 patients	–	Medical Imaging	Fetal abnormalities	AI-assisted fetal ultrasound planes
Rajab et al. (2023)	Uganda	Performance evaluation	2207 patients	–	Infectious diseases	Malaria	Interpretable Machine Learning (IML) models
Kiemde et al. (2022)	Burkina Faso	Randomized controlled diagnostic trial	Block size of 20, 30, or 40 subjects in random order	1 year	Infectious diseases	Febrile illness	AI-assisted intervention in a two-step malaria RDT PfHRP2/pLDH and point-of-care tests
Liu et al. (2022)	Senegal	Field evaluation	32 water bodies	2016–2019	Spatial analysis	Schistosomiasis	Deep learning segmentation of high-resolution satellite imagery and drone technology
Singh and Mars (2012)	South Africa	Model evaluation	600 clinicians	–	Infectious diseases	HIV/AIDS	Physician-administered AI-based decision support system
Esber et al. (2023)	Uganda, Kenya, Tanzania, and Nigeria	Cohort	1571 patients on ART	2013–2020	Infectious diseases	HIV/AIDS	Machine learning-based algorithms (lasso-type regularized regression and random forests)
Turbé et al. (2021)	South Africa	Pilot (cross-sectional)	60 nurses and community health workers	–	Infectious diseases	HIV/AIDS	Deep learning technology
Stockman et al. (2022)	Mozambique and Nigeria	Implementation science	360000 patients	2010–2019	Infectious diseases	HIV/AIDS	Machine learning technology Forest model
Tallam et al. (2021)	Senegal	Performance evaluation	5500 images of snails and 5100 images of cercariae	2015–2019	Imaging	Schistosomiasis	Deep learning-based convolutional neural networks (CNNs)
Makau-Barasa et al. (2023)	Nigeria	Performance evaluation	869 patients	–	Microscopy	Schistosomiasis	AI-assisted microscope (AiDx NTDx multi-diagnostic Assist microscope)
Niazkar and Niazkar (2020)	South Africa	Performance evaluation	–	–	Infectious diseases	COVID-19	Artificial Neural Networks (ANN)
Mulenga et al. (2023)	Zambia	Performance evaluation	1433 COVID-19 hospitalized patients	2020–2021	Infectious diseases	COVID-19	Machine learning algorithms
Ibrahim et al. (2023)	Morocco, Sudan, Namibia, South Africa, Uganda, Rwanda, Nigeria, Senegal, Gabon and Cameroon	Performance evaluation	–	2020–2022	Infectious diseases	COVID-19	Machine learning models
Elahi et al. (2022)	Tanzania	Performance evaluation	2972 patients	–	Non-communicable diseases	Traumatic Brain Injury	A locally derived machine learning-based prognostic model
Bellemo et al. (2019)	Zambia	Performance evaluation	76370 retinal fundus images from 13099 patients	2010–2013	Non-communicable diseases	Diabetic retinopathy	Convolutional neural networks

(continued on next page)

Table 2 (*continued*)

Author/Year	Country	Study design	Sample size/ number of patients	Study duration	Specialty	Disease	AI algorithm/model
Ebrahim and Derbew (2023)	Ethiopia	Performance evaluation	1523 patients with type-2 diabetes and 716 without type-2 diabetes	February to June of 2021	Non-communicable diseases	Type-2 diabetes	The Decision tree pruned J48, K-nearest neighbor, Naïve Bayes, Binary logistic regression, Support vector machine, Artificial neural network, and Random forest machine learning algorithms
Folson et al. (2023)	Ghana	Performance evaluation	36 adolescent girls	–	Non-communicable diseases	Malnutrition	A mobile AI dietary assessment application known as Food Recognition Assistance and Nudging Insights (FRANI)
Porras et al. (2021)	The Democratic Republic of the Congo	Performance evaluation	132 patients	–	Facial Analysis	Down syndrome	An in-house mobile application using AI-assisted facial analysis technology
Njoroge et al. (2023)	Kenya	Cohort	500 health workers	12 months	Non-communicable diseases	Mental health	A mobile application modelled to use sensor stream signatures
Sukums et al. (2015)	Ghana and Tanzania	Longitudinal	61 and 56 health workers at the midterm and final assessment	2011–2013	Maternal and neonatal	Antenatal and intrapartum abnormalities and complications	AI-assisted electronic clinical decision support system (eCDSS)
Zakane et al. (2014)	Burkina Faso	Qualitative	45 informant interviews	2011–2012	Maternal and neonatal	Antenatal and intrapartum abnormalities and complications	A computerized clinical decision support system (CDSS)
Mohammed et al. (2021)	The Gambia	Performance evaluation	11012 children with clinical pneumonia	–	Maternal and neonatal	Pneumonia	Neural Network Prediction Model
O'Donovan et al. (2022)	Uganda and Kenya	Descriptive development and validation	12 community health workers from Uganda and 25 from Kenya	2020–2021	Supervision	Community management of diseases	An open-access predictive machine learning web application

(Folson et al., 2023; Niazkar & Niazkar, 2020; Sendra-Balcells et al., 2023; Singh & Mars, 2012). Nineteen studies had strong quality (Bellemo et al., 2019; Ebrahim & Derbew, 2023; Elahi et al., 2022; Esber et al., 2023; Ibrahim et al., 2023; Kiemde et al., 2022; Liu et al., 2022; Makau-Barasa et al., 2023; Mohammed et al., 2021; Mulenga et al., 2023; Njoroge et al., 2023; O'Donovan et al., 2022; Porras et al., 2021; Rajab et al., 2023; Stockman et al., 2022; Sukums et al., 2015; Tallam et al., 2021; Turbé et al., 2021; Zakane et al., 2014).

3. Findings and discussion

3.1. *Current application of medical AI in sub-Saharan Africa*

Since the advent of big-data-bound technologies across the globe, SSA has harnessed these technologies to enhance livelihoods. Computer-assisted platforms and AI have been widely used in SSA in diverse specialties in healthcare and medicine. This review profiles the application of these technologies in medical imaging, diagnosis of infectious and non-communicable medical conditions, disease outbreak surveillance and response systems, forecasting, public health point-of-care diagnostics uptake, and maternal and neonatal care.

3.1.1. *Medical imaging*

AI-powered applications have impacted several specialties of medical imaging, such as brain imaging, cancer, chest imaging, and cardiology (Houssein et al., 2021; Martin-Isla et al., 2020; Zhang et al., 2020). However, the focus has always been on high-resource settings. Most medical imaging diagnostic platforms, such as the use of X-rays, are known to offer high and acceptable diagnostic performance (sensitivity and specificity). However, there may be human variations and inconsistencies in test performance and radiological interpretation of test outputs, mainly due to the different competencies and technical experiences of the radiographers and radiologists. Also, in resource-limited settings, including SSA, specialist opinion and the required radiological expertise may be lacking, particularly in highly disease-burdened and hard-to-reach communities (Pedrazzoli et al., 2017). The application of AI-assisted algorithms has been tested and evaluated in attempts to address these limitations.

In Lesotho and South Africa, computer-aided detection (CAD) software built on AI has significantly been applied in reading and interpreting chest X-ray results for detecting chest X-ray tuberculosis (TB) pathology (Glaser et al., 2023). This medical AI system has improved TB case findings and real-time diagnosis with limited human intervention or the need for specialist radiologists who are limited in high-TB-burdened settings such as South Africa.

Similarly, a new framework for medical AI models was built for clinicians to detect and diagnose fetal abnormalities using fetal ultrasound planes in five (5) African countries (Egypt, Algeria, Uganda, Ghana, and Malawi) using local datasets from these countries (Sendra-Balcells et al., 2023). These AI models were transferred from high-income countries such as Denmark and the UK and applied in low-income settings.

3.1.2. Infectious diseases

Several AI-assisted clinician decision-making and diagnostic algorithms have been proposed, evaluated, and implemented in SSA for diagnosing and managing various infectious diseases. For example, Friedman proposed a promising strategy for diagnosing most infectious diseases in rural settings of SSA using computer-assisted medical diagnosis tools (Friedman, 2009). He introduced several carefully selected computer-assisted diagnosis and physician decision support systems (DiagnosisPro, ASTI, DXPLAIN, EGADSS, GIDEON, Isabel, and PAIRS) in SSA to facilitate efficient disease diagnosis and address the health workforce deficits.

Specifically, in malaria predictions and diagnostic interpretations, a study in Uganda used Interpretable Machine Learning (IML) models to predict and interpret severe malaria predictions based on large data and deep learning (Rajab et al., 2023). The researchers employed Explainable Artificial Intelligence (XAI) techniques such as the Shapley Additive Explanation (SHAP) and Local Interpretable Model-agnostic Explanation (LIME) to improve the reliability of malaria predictions and the early detection of severe malaria. The SHAP technique, rooted in game theory's Shapley values, equitably assigns each feature's influence on predictions, providing both local and global consistent interpretability (Lundberg & Lee, 2017). In contrast, LIME creates fast and flexible local approximations using simpler models to explain individual predictions across any machine learning model (Ribeiro et al., 2016).

Kiemde and colleagues are currently testing a hypothesis that seeks to improve febrile illnesses among children under 5 and to address antimicrobial resistance (AMR) in Burkina Faso (Kiemde et al., 2022). This will be done by developing and evaluating an AI-assisted algorithm (intervention) in a two-step malaria RDT PfHRP2/pLDH and point-of-care tests for detecting malaria and bacterial infections respectively. The AI intervention will use large data on patients' clinical information for example, clinical presentations, clinical history, and laboratory test results using varying biomarkers such as C-reactive protein, white blood cell count, and specific bacterial point-of-care test outcomes.

In schistosomiasis control, an AI-powered computer vision model built by merging deep learning segmentation of high-resolution satellite imagery and drone technology was employed to map the spatial distribution of schistosome-inhabited vector snails in the Senegal River Basin (Liu et al., 2022). This model was aimed at locating the vector snails that aid in the transmission of schistosomiasis to give directions for control interventions by stakeholders involved. Similarly, a proof of concept study was conducted in Senegal to prove that deep learning-based convolutional neural networks (CNNs) can effectively classify vector snails and schistosoma parasites (Tallam et al., 2021). The CNN was fed and trained with 5500 images of different genera of schistosomal vector snails harvested from the Senegal River Basin together with images of non-human schistosomiasis vector snails. The CNN model learned and achieved 99% accuracy in classifying snails and 91% accuracy in classifying the schistosoma parasites. Furthermore, an AI-assisted microscope (AiDx NTDx multi-diagnostic Assist microscope) was evaluated on performance regarding digital detection of S*chistosoma haematobium* and quantification of schistosomal eggs in Nigeria (Makau-Barasa et al., 2023). The evaluation further considered the ability to auto-focus, auto-scan, and register images into its system and process them using AI, and automatic parasite count using two types of microscopes (semi-automated and fully automated). The semi-automated microscope had 90.3% and 89% sensitivity and specificity respectively whereas the fully automated AiDx Assist microscope had 98% and 99% sensitivity and specificity respectively. Similarly, there was a significant correlation of egg count of both semi-automated ($r = 0.93$, $p \leq 0.001$) and fully automated ($r = 0.89$, $p \leq 0.001$) AI-assisted microscopes with those of the conventional microscope.

Likewise, AI seeks to enhance HIV management in SSA. For instance, a proposed study in South Africa sought to develop a physician-administered AI-based decision support system tool to effectively manage HIV patients on antiretroviral therapy (ART) (Singh & Mars, 2012). This technology sought to estimate HIV prognosis based on large data of CD4 count, HIV genomic sequence, and information on ART resistance. Moreover, deep learning technology was implemented to complement the diagnostic performance of point-of-care (POC) diagnostics for diagnosing HIV in South Africa (Turbé et al., 2021). The deep learning technology demonstrated 97.8% and 100% sensitivity and specificity respectively for accurately interpreting the HIV POC test results. This algorithm conforms with the real-time connectivity component embedded in the new foundational principle for implementing REASSURED diagnostics in SSA (Land et al., 2019; Otoo & Schlappi, 2022). Also, two machine learning-based algorithms' (lasso-type regularized regression and random forests) ability to predict HIV viral failure and its associated factors were compared in Uganda, Kenya, Tanzania, and Nigeria (Esber et al., 2023). At least 1000 copies/ml viral load for persons living with HIV (PLWHIV) and receiving ART for at least 6 months was considered as viral failure. The lasso regression model performed better than the random forest in identifying viral failure. Furthermore, machine learning technology was implemented to predict and identify ART clients with a higher risk of ART compliance and loss to follow-up in Nigeria and Mozambique health systems (Stockman et al., 2022). High precision recalls of 0.65 and 0.52 were recorded in Mozambique and Nigeria respectively using the Random Forest model. These were against loss to follow-up (LTFU) rates of 23% and 27% respectively.

In the advent of COVID-19, case prediction AI models using Artificial Neural Networks (ANN) were proposed and applicability tested in several countries including South Africa (Niazkar & Niazkar, 2020). The ANN models were designed to forecast COVID-19 confirmed cases while considering the 14-day incubation period. The 7th, 12th, and 14th models had the best performance out of the 14 prediction models evaluated. Similarly, machine learning algorithms were employed to predict mortality rates of hospitalized COVID-19 patients in Zambia (Mulenga et al., 2023). Seven (7) machine learning models including XGBoost (XGB), decision tree (DT), gradient boosting (GB), random forest (RF), Naïve Bayes (NB), support vector machines (SVM), and logistic regression (LR) were evaluated. The XGB model performed best in predicting the COVID-19 mortality rates in Zambia with 92.3% accuracy, 94.2% recall, 92.4% F1-Score, and 97.5% area under the receiver operating characteristic curve (ROC_AUC). Moreover, four (4) machine learning models were evaluated in Morocco, Sudan, Namibia, South Africa, Uganda, Rwanda, Nigeria, Senegal, Gabon, and Cameroon to adequately predict daily COVID-19 cases (Ibrahim et al., 2023). The ANN, adaptive neuro-fuzzy inference system (ANFIS), SVM, and conventional multiple linear regression (MLR) models were evaluated based on their accuracy in predicting new cases and new variants. Though ANFIS better predicted COVID-19 new cases, it was revealed that some models produced better outcomes when used in an ensemble for example ANN-E and SVM-E.

3.1.3. Non-communicable diseases and injuries

In addition, medical AI has been applied in the assessment of cancers, renal diseases, metabolic derangements, retinopathies, injuries, and among others. For example, in Tanzania, a locally derived machine learning-based prognostic model using large data from a traumatic brain injury (TBI) registry of the Kilimanjaro Christian Medical Center (KCMC) was developed and compared with foreign online-based decision support technologies such as the corticosteroid randomization after significant head injury (CRASH) and international mission for prognosis and clinical trials in traumatic brain injury (IMPACT) (Elahi et al., 2022). This development was to reduce the long triage, diagnosis, and surgery duration for TBI patients. The KCMC model had the best discrimination (area under the curve), could be calibrated like the other two models, and performed similarly to the CRASH model.

In Zambia, an AI model made up of two convolutional neural networks (VGGNet architecture and a residual neural network architecture) using deep learning was evaluated for diagnosing diabetic retinopathy (Bellemo et al., 2019). This technology used large data of 76000 color fundus images of patients diagnosed with diabetes from both foreign and local sources (Singapore and Zambia) to classify diabetic retinopathy. The AI system demonstrated promising results, recording an area under the curve of 0.973 for referable diabetic retinopathy and sensitivities of 99.42% for vision-threatening diabetic retinopathy and 97.19% for diabetic macular edema. The system was also able to identify systemic risk factors with similar accuracy to human graders, highlighting its potential in aiding early diagnosis and reducing the burden on ophthalmologists in SSA.

Supervised machine learning algorithms were applied in Ethiopia to classify and predict type 2 diabetes (Ebrahim & Derbew, 2023). These algorithms (Decision tree pruned J48, K-nearest neighbor, Naïve Bayes, Binary logistic regression, Support vector machine, Artificial neural network, and Random Forest) were fed with 2239 datasets made up of 1523 people with type-2 diabetes and 716 people without type-2 diabetes. Random forest emerged as the best classification and prediction algorithm with a 93.8% correct classification rate and 98% sensitivity.

A mobile AI dietary assessment application known as Food Recognition Assistance and Nudging Insights (FRANI) was evaluated among adolescent females 12–18 years old in Ghana against two (2) models thus weighed records (WR), and multipass 24-h recalls (24HR) using different dietary nutrient compositions (Folson et al., 2023). The accuracy of the AI-assisted FRANI mobile application was equivalent to those of WR and 24HR hence could efficiently assess and estimate dietary nutrient intake in adolescent girls in Ghana.

In the Democratic Republic of Congo, an in-house mobile application using AI-assisted facial analysis technology was implemented for screening and detecting Down syndrome among the local population (Porras et al., 2021). Using deep learning approaches, frontal facial images of presumed Down syndrome normative persons as the control arm and suspected Down syndrome cases were fed into the mobile application. The software produced 91.67%, 95.45%, and 87.88% accuracy, sensitivity, and specificity respectively.

Medical AI and deep learning models have been proposed to predict mental health outcomes in Kenya (Njoroge et al., 2023). A mobile application is modelled to use sensor stream signatures to predict the risk of depression and mood abnormalities among healthcare practitioners in Kenya. This application if fully implemented will scale up real-time detection and diagnosis of mental disorders among healthcare workers and boost economic liberation in Kenya and SSA as a whole.

3.1.4. Maternal and neonatal healthcare

Several advancements have been made in the application of AI-powered, deep-learning, and machine-learning systems in maternal and neonatal care in SSA. These systems range from triaging algorithms in antenatal care to perinatal assessments to ensure both the baby's and mother's safety and survival; and ultimately reduce maternal and neonatal mortality rates in SSA. Maternal health intervention using the Quality of Maternal and Prenatal Care: Bridging the Know-Do Gap (QUALMAT) project was designed and evaluated in Ghana and Tanzania (Sukums et al., 2015). This project introduced an AI-assisted electronic clinical decision support system (eCDSS) for antenatal and perinatal care to help reduce maternal and neonatal mortality in sub-Saharan Africa. The project trained healthcare workers who provide antenatal and perinatal care to patients in six primary healthcare facilities in rural communities.

Similarly, a computerized clinical decision support system (CDSS) was introduced and evaluated among rural maternal and neonatal care professionals in Burkina Faso (Zakane et al., 2014). This medical AI system was introduced to augment the care given by maternal and neonatal healthcare providers in rural settings to improve the quality of services.

In Gambia, an online web-based neural network-based pneumonia mortality prediction triage tool was migrated and implemented as an entirely offline mobile application (Mohammed et al., 2021). This development aimed at assisting medical staff during patient triaging for admission to better predict the risk of death of children diagnosed with pneumonia for rapid intervention in real-time to save lives.

3.1.5. Monitoring and supervision

While most AI-powered algorithms are targeted for specific medical conditions or diseases, others are implemented to monitor and strengthen healthcare programs and systems. For example, in Uganda and Kenya, an open-access web-based machine learning application was developed to effectively supervise community health workers (m-Health-facilitated supervision) (O'Donovan et al., 2022). The application uses 3429 coded digital supervisory interactions between community health workers and their supervisors and engages in deep learning to ensure that the community healthcare workers function effectively and meet set targets.

3.2. The enablers of medical AI in SSA

It is well understood that the implementation of any medical technology in a healthcare system requires that some conditions be met. Major themes emerged, including the availability of enough and quality data and support from institutions, particularly in financing, regulation, education, and competency training.

3.2.1. Availability of large and quality clinical datasets

AI-powered projects thrive on the availability of large and quality data. AI models are trained using data, and as such, the quality of their output is a function of the data they are fed (Owoyemi et al., 2020). Currently, most health facilities in SSA run on different information management systems, ranging from non-digitized (paper-based folders) to limited facility-specific electronic information management systems (Akanbi et al., 2012).

Although, SSA may not have a common health information system, either through a donor-sponsored or self-sponsored program, South Africa, Benin, Botswana, Ghana, Malawi, Mozambique, Rwanda, Sierra Leone, Tanzania, Zambia, Zanzibar, and Zimbabwe have implemented the District Health Information System software version 2 (DHIS 2) as their health information system (Koumamba et al., 2021). However, most routinely collected country-specific data from health ministries in SSA are challenged with issues related to quality, completeness, uniformity, and timeliness as demanded for national, regional, and global policy formulations (Mbondji et al., 2014).

The COVID-19 pandemic exposed the poor digital health systems in SSA, which led to the main shift in approach to coordinate the surveillance systems in SSA with that of the global health systems. Several public health information algorithms were developed and implemented in SSA. For example, the African Union launched a "saving lives, economies, and livelihoods" campaign in 2020 to safeguard the African continent using a common health status and mobile global health information platform known as the PanaBios (AU, 2020). Similarly, Ghana and Nigeria have fully adopted an open-source mobile eHealth information system SORMAS (Surveillance Outbreak Response Management and Analysis System) to manage and control disease outbreaks (Barth-Jaeggi et al., 2023). However, Côte d'Ivoire, Nepal, Tanzania, and Tunisia are currently piloting and partially implementing SORMAS at the sub-national level (Barth-Jaeggi et al., 2023).

Currently, the Africa CDC is supporting member states to leverage digital health technologies to address the loopholes in the health information management systems in the continent (Africa CDC, 2023). For medical AI to be successfully implemented in SSA, digital health and data management systems must be strengthened to generate local data for training the systems. For this to be achieved, public health units and health information sections should be empowered to switch from manual documentation to computerized information systems.

3.2.2. Financial and institutional support

Globally, AI systems are expensive and hence require a strict financial commitment to implement in low and middle-income countries, particularly in SSA whose health systems commonly function on donor support. Several AI components including data collection, hardware, software, labor, testing, deployment, training, and maintenance among others are required to fully mount and implement an AI-powered digital system (Reilly, 2023). It costs not less than USD15000, USD40000, and USD80000 for a low-level complex, medium-level complex, and high-level complex AI respectively (RisingMax, 2023). However, the health and economic impact outweighs the cost of implementation. For example, in the United States of America, the use of medical AI potentially could save between USD200 billion and USD360 billion of costs of healthcare annually (Alnasser, 2023). In addition, medical AI tools have been demonstrated to produce health incremental gains compared with non-AI tools. For example, an AI-powered screening tool for colorectal cancers demonstrated a 4.8% cost-effective incremental gain compared to a non-AI screening tool (Areia et al., 2022). Similarly, an autonomous AI tool for screening retinopathies in premature infants and low birthweight neonates was USD34 more cost-effective than assessment by ophthalmoscopy (Morrison et al., 2022).

For AI systems to be deployed and maintained in hospital laboratories, there should be investments in research, infrastructure, and training programs (Herman et al., 2021). These investments are necessary to ensure that the AI systems are reliable, sustainable, accurate, and efficient. The training programs should be designed to equip the laboratory staff with the necessary skills to operate and maintain the AI systems as stewards. The infrastructure should be robust enough to support the systems and ensure that they are always available when needed. The research should be focused on improving the systems' accuracy, reliability, and efficiency, as well as identifying new use for the technology.

3.2.3. Regulatory framework and ethical approval

Several ethical issues have been discussed since the advent of AI-powered algorithms in the global web space. These discussions have been prominent especially in healthcare research (Scott et al., 2020) and academia (Khan, 2023). For example, there is a rising trend of misinformation and disinformation based on the potential threat of AI-generated images, videos, and audio in the digital space (Gonzalez, 2023; Ramirez et al., 2023). In healthcare, there are concerns about a breach of patient confidentiality through the exposure of patients' private health information in the cloud bundled in large data to be used by computer algorithms (Kitsios et al., 2023). A digital health policy implemented across the SSA region would potentially guide the ethical deployment and monitoring of digital health strategies before AI can be implemented in the medical laboratory (Owoyemi et al., 2020). This is because the AI systems can operate, to some degree, autonomously from the human health care practitioner, and use machine learning to generate new, often unforeseen analyses and predictions (Donnelly, 2022).

Leaders in SSA countries should learn from global AI readiness experiences and formulate SSA-contextual regulatory frameworks and standards for the development and deployment of AI in healthcare to ensure patient safety and data privacy. For example, the European Union (EU) is leading AI policy formulations in the global AI landscape such as the EU Digital Services Act, the EU Digital Markets Act, and the AI Act; the USA has Executive Order 13859, National Artificial Intelligence Initiative, the National AI Advisory Committee, and the AI Consumer Privacy Act; China has the Cyberspace Administration, and the Chinese Association for Artificial Intelligence (Goriola et al., 2023).

3.2.4. Training and education

It is critical to provide healthcare personnel with the required training and knowledge of AI technology. This could be implemented through the institution and Government-sponsored tertiary education and continuous professional development for laboratory professionals (Charow et al., 2021). This guarantees that the trained personnel can properly implement these technologies into their practice and comprehend the strengths and limitations of the AI systems. Also, the role of the medical scientist within the AI medical setup should be clearly defined. Clinical scientists will embrace and integrate AIs into their practice if they are made to understand that their future is not in peril, but the systems will only enhance their output (Cutamora et al., 2023). These initiatives will help to improve the quality of healthcare and patient outcomes.

3.3. Challenges to the application of medical AI in SSA

Despite the enabling factors to potentially implement successful AI-powered algorithms in the clinical settings of SSA, several challenges impede their acceptance and implementation.

3.3.1. Data unavailability

The lack of complete, unbiased, and timely digital-based structured data in the healthcare systems of SSA is a major challenge to meeting the basic requirement for implementing AI-powered systems (Musa et al., 2023). The lack of reliable and comprehensive data makes it difficult to develop effective healthcare policies and programs, allocate resources, and monitor progress. Many health facilities in SSA, particularly health facilities in hard-to-reach settings are now integrating digital health records into their system (Akanbi et al., 2012). However, a few others still depend on the folder (manual) methods of keeping patient details and health information. Given that, large and quality data is required for training AI models, it is a significant hurdle, that must be overcome for integrating medical AIs into hospital laboratories in SSA.

3.3.2. Data security issues

The usage of information and communication technologies (ICTs) in Africa is one of the drivers of escalating privacy issues. Typically, public anxieties about people's privacy have been fuelled by the huge gathering of personal information and the relatively straightforward possibilities for the exploitation of such information (Makulilo, 2012). This is a major concern, particularly in the healthcare sector, where sensitive information about patients is collected and stored. For the successful implementation of medical AI in SSA, these concerns need to be addressed. It is important to establish robust data protection policies and regulations that will safeguard the privacy of individuals. Additionally, healthcare providers need to implement strict and appropriate security measures to protect patient data from unauthorized access, use, or disclosure.

3.3.3. Resource constraints

A major challenge that limits the use of Medical AI in SSA is poor financial, infrastructure, and digital-skilled health workforce resourcing (Cerf, 2021; Oleribe et al., 2019). The use of AI in healthcare is gaining momentum, and governments, healthcare systems, and private organizations understand the value of these technologies. However, few among them have the resources to purchase these AI tools, making their integration a challenge.

3.3.4. Regulatory hurdles

Lack of AI regulations in SSA poses a potential risk to the successful implementation of medical AI. Comparably, the application of AI in the healthcare setting comes with great risks. Diagnosis and treatment decisions can have deadly consequences if errors are made during analysis (Kaur et al., 2021). The ethical dimensions of AI in healthcare require careful attention in the development and application of algorithms. Overcoming these challenges demands not only the development of comprehensive regulatory frameworks, but also the establishment of collaborative networks, capacity building, and an unwavering commitment to prioritizing patient safety in healthcare AI applications.

3.3.5. Poor access to internet connectivity

Poor access to reliable internet connectivity has been the worst challenge in SSA's journey to digital transformation. Only 36% of the SSA population have access to broadband internet connectivity, however, affordability issues remain unresolved (World Bank, 2023). The Internet connectivity crisis has hindered the implementation of the fourth industrial revolution (4IR) in low and middle-income countries, especially SSA (Sehlako et al., 2023) and healthcare systems (Mwanza et al., 2023). Although the technological advancements in AI systems may now permit a limited few complex algorithms to run offline using mobile applications (Jain et al., 2021), the majority of medical AI-powered systems require internet access (Manickam et al., 2022).

3.3.6. Poor acceptance and perceptions

Several misconceptions and myths have been formed and propagated against the global acceptance and implementation of AI hence clouding the revolutionary benefits AI seeks to bring. These have created confusion, fear, and panic, particularly in SSA largely through misinformation fuelled by socio-cultural influences (Ade-Ibijola & Okonkwo, 2023). For example, the misconception that AI will erase human existence and, the lack of trust in AI systems due to the absence of human personal emotions such as empathy, among others, have slowed down the acceptance and use of AI-powered technologies (Bewersdorff et al., 2023). In SSA, a predominantly high proportion of public health professionals believe although medical AI will improve their task performance, job security is a concern (Mwase et al., 2023).

3.3.7. Digital illiteracy

Digital literacy forms the backbone of Africa's readiness to meet the current trends in global digitization and to adopt and implement AI and machine learning. The SSA region has heterogeneous digital-skilled personnel in individual settings. However, the region records the poorest digital-skilled population globally (Madden & Kanos, 2020). South Africa, Nigeria, and Kenya have on average the highest digital literacy in SSA according to the World Bank's 2021 report on the Future of Work in Africa (Choi et al., 2020). Other countries such as Ghana, Rwanda, and Mozambique are gradually harnessing digital technologies largely through international collaborations and donor support systems to transform their digital space and ultimately create digital economies (MoCD, 2023; World Bank, 2021).

3.4. The opportunities to apply medical AI to improve healthcare systems in SSA

On the other hand, medical AI provides several opportunities to ultimately provide equitable population health, especially in poorer communities. Brain drain has resulted in the loss of skilled health workforce in developing countries including SSA as it continues to drag the economic development of these countries (Docquier et al., 2007). This is a significant problem in the health sector of SSA as most healthcare workers are not satisfied with the conditions of service in the region. Medical AI offers the distinct advantage of streamlining testing processes, leading to a significant reduction in the personnel required for test administration and adequately remunerating and well-resourcing the few (Cutamora et al., 2023). By automating routine tasks and enhancing efficiency in data analysis, medical AI not only optimizes resource utilization but also allows healthcare professionals to focus their expertise on more complex and critical aspects of patient care. This promotes competency development through continuing professional development and refresher training to stay abreast with current trends (Feldacker et al., 2017).

Above all, the willingness of healthcare professionals especially, medical laboratory personnel to adapt and build competency to work with AI-powered algorithms gives hope for the effective implementation of medical AI in the healthcare and laboratory space in SSA. These are evident in the active participation in conversations surrounding AI with others leading AI development, evaluation, and use (Barth-Jaeggi et al., 2023; The Citizen, 2023; WEC, 2022). However, these are only feasible when the challenges discussed are adequately addressed and the needed facilities and resources are provided.

3.5. Implications of medical AI for medical laboratory practice

The implications of digitization and medical AI in medical laboratory practice are numerous, with great prospects for enhancing diagnosis, patient care, and operational efficiency (Alowais et al., 2023; Isbılen Basok, 2020). Integrating artificial intelligence will revolutionize laboratory medicine practice in SSA.

3.5.1. Improved diagnostic efficiency

AI-based laboratory testing improves the efficiency of diagnosis in the medical space because they have the potential to improve a test's turnaround time, quality, and cost (Rhoads, 2020). AI-powered diagnostics have gained traction and proven to produce better diagnostic performance than non-AI routine laboratory procedures (McDonald et al., 2017; Rabbani et al., 2022). AI-powered laboratory algorithms using machine learning approaches have successfully and accurately predicted laboratory results (Rabbani et al., 2022) and reference values (Yang et al., 2013) based on available large, structured, and quality data. For example, an AI-powered neural network model learned from routine complete blood count results to accurately predict serum iron concentration and iron deficiency anemia (Azarkhish et al., 2012). Similarly, the AI-assisted serum lipid analysis algorithm accurately estimated low-density lipoprotein cholesterol (LDL-C) through the deep neural network using large datasets from the Korean National Health and Nutrition Examination Survey and the Wonju Severance Christian Hospital (Lee et al., 2019).

In addition, AI-assisted diagnostic algorithms have the potential to address probable patient and sample misidentification which may result in adverse and sometimes fatal outcomes for patients. Pre-analytical errors, which usually center around patient and specimen identification, are mostly predominant among laboratory errors (Bonini et al., 2002). Patient and specimen misidentification is a serious issue that has the potential to cause detrimental health outcomes to patients (Valenstein et al., 2006) and may have repercussions on laboratory personnel. However, AI models have been trained to identify and manage patients and specimens with a focus on identifying mislabelled laboratory samples (Farrell, 2021).

In resource-limited settings especially in SSA, culture and sensitivity testing to diagnose urinary tract infections (UTI) have a success rate of approximately 30% (McDonald et al., 2017). This infers that, out of a hundred people with UTIs, there is a probability that 70% may be misdiagnosed, and this negatively affects healthcare delivery. Also, many bacteria are morphologically diverse and may adapt and make some morphological changes (Treebupachatsakul & Poomrittigul, 2020), making microscopic identification challenging. Recently, machine learning approaches have been demonstrated to accurately detect bacteremia and mycoses (over 98.7% sensitivity) using large, multicentre in-patient data (Bhavani et al., 2020). This technology has the potential to revolutionize bacteria and fungi cultures to maximize test outcomes for efficient patient management. Again, this is proof that the pitfalls in microbial identification in medical laboratories can be improved greatly with AI.

Finally, the use of AI-modelled wearables (Dunn et al., 2021; Picard & Boyer, 2021) to estimate and predict laboratory results and the gradual implementation of point-of-care diagnostics have the potential to democratize access to diagnostics and healthcare in general in poor regions particularly hard-to-reach settings of SSA (Dincer et al., 2017; Mashamba-Thompson, 2022).

3.5.2. Quality assurance and test validation

In most jurisdictions, AI and machine learning models have been used to revolutionize quality control systems and have been demonstrated to effectively validate routine laboratory test results. For example, a machine learning-supported patient-centered real-time quality control system accurately detected analytical errors for biochemistry test biomarkers albumin (71.3% sensitivity and 99.6% specificity), and glucose (95.2% sensitivity and 98.7% specificity), among others (Zhou et al., 2022). Similarly, quality control systems for testing complete blood count biomarkers using combined evaluation of delta data and machine learning produced 99% accuracy, 99% sensitivity, and 99% specificity (Liang et al., 2022). Also, AI-assisted neural networks and tree-based algorithms have been employed in verifying the validity of laboratory results, distinguishing micro-clotted blood samples from non-clotted samples, and identifying mislabelled samples (Rabbani et al., 2022).

3.5.3. Interpretation of laboratory test outputs

Recent studies have revealed the application of medical AI and machine learning technology in the interpretation of laboratory test results. These augment the specialist knowledge of both clinicians and laboratory professionals. For example, machine learning algorithms on hematological testing have accurately predicted and interpreted blood-based test results for differential diagnosis of hematologic diseases (Gunčar et al., 2018). At the onset of the COVID-19 pandemic, a smartphone-based application (xRCovid) was developed and evaluated on its accuracy in reading and interpreting COVID-19 rapid diagnostic test (RDT) results using machine learning technology (Mendels et al., 2021). This application produced between 97.6-100% and 99–100% sensitivity and specificity respectively using eleven (11) different RDT models which increased the test uptake and boosted the test confidence to be used as a self-test (Mendels et al., 2021). Elsewhere, a tree-based machine learning model was used to classify steroid profiles in urine with 87% accuracy in diagnostic performance and interpretation (Wilkes et al., 2018).

3.5.4. Better management of laboratory records and patient data

Medical AI and deep learning platforms have been integrated into laboratory information management systems. These smart systems can be used to analyze large amounts of data that include population heterogeneities and would allow a revolution in the healthcare field in real-time (Pereira et al., 2021). For example, a tree-based machine learning technology was used to accurately identify 85% of unlabelled laboratory results in a laboratory database (Parr et al., 2018). Similarly, using machine learning algorithms, Logical Observation Identifiers Names and Codes (LOINCs) can identify data of interest through adjudication processes devoid of the stress of manual review and data search (Fillmore et al., 2019). Better management of patient records will allow for early detection, prevention, and management of diseases.

3.5.5. Cost-effective laboratory diagnostics

Medical AI has produced cost-effective laboratory diagnostics in the differential diagnosis of several diseases. For example, laboratory malaria diagnosis using machine learning-powered digital in-line holographic microscopy rapidly and better detected malaria-infected red blood cells compared with conventional staining and microscopy (Go et al., 2018). In addition, this technology-driven algorithm is more sensitive and cost-effective in diagnosing malaria. Similarly, the economic evaluation of an AI model was performed in cytology testing for cervical cancer screening (Shen et al., 2023). The evaluation established that the AI-assisted screening algorithm is more cost-effective with an ICER of USD8790/QALY gained compared with the conventional screening method (Shen et al., 2023). While the initial investment in AI deployment may necessitate resources, the long-term advantages in terms of cost savings, operational efficiency, and enhanced results may surpass these early costs (Cutamora et al., 2023).

4. Limitations

Reviews might unintentionally miss out on valuable information because they stick to specific search scopes and eligibility criteria. In this study, for instance, some good studies in non-English languages, grey literature, and unpublished articles were excluded.

5. Conclusion

Medical AI can revolutionize the practice of medical laboratory science in the SSA. Several studies have proven that AI can be integrated into the medical space in SSA. Despite the proven importance and advantages of incorporating AI in laboratory practice, many hurdles need to be overcome before the integration can be complete. Education and competency training, ethical consideration, the generation of local data, and investments in infrastructure and technology must be achieved before the successful implementation of medical AI in laboratory practice in SSA.

6. Recommendations for the application of medical AI in medical laboratories in SSA

To allow for the effective integration of medical AI into laboratory practices in SSA, several strategic policies must be implemented. To begin with, comprehensive education and training programs should be established to equip medical laboratory professionals with the necessary knowledge and skills in AI. The training institutions in SSA should develop relevant curricula and training programs to equip medical laboratory professionals with AI skills. Governments should allocate resources for education and competency training programs, as well as invest in infrastructure and technology. Simultaneously, the formulation and implementation of ethical guidelines and regulatory frameworks specific to the region are vital to ensuring responsible AI usage. Encouraging the generation of structured and quality local healthcare data for training and validating AI algorithms, coupled with investments in healthcare infrastructure, will enhance the seamless integration of AI into laboratory workflows. Additionally, technology service providers, such as internet service providers, play a vital role in offering equitable and accessible tailored solutions and support for the successful implementation of medical AI in laboratory practice in SSA. Making AI technologies more accessible and affordable, along with promoting public and professional awareness, will contribute to widespread acceptance. Collaborative research initiatives, governmental support, and capacity building in AI governance are integral components. Implementing pilot programs, followed by continuous evaluation, will allow for the refinement of AI applications based on real-world performance. By collectively addressing these recommendations, stakeholders can overcome existing hurdles and usher in a new era of enhanced healthcare through the successful integration of medical AI in SSA.

Ethics statement

An ethics statement is not applicable because this study is based exclusively on published literature.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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No data was used for the research described in the article.

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