Adoption of Artificial Intelligence in Primary Health Care System in Sub-Saharan Africa: Influencing Factors and Emerging Best Practices

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Adoption of Artificial Intelligence (AI) in Primary Health Care (PHC) System in Sub-Saharan Africa (SSA): Influencing Factors and Emerging Best Practices

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Public Health and Health Equity by

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Declaration:

Where other people's work has been used, this has been carefully acknowledged and referenced in accordance with academic requirements.

The thesis 'Adoption of Artificial Intelligence in Primary Health Care System in Sub-Saharan Africa (SSA): Influencing Factors and Emerging Best Practices' is my own work.

Signature:

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Abstract

Background:

Artificial Intelligence (AI) is transforming global healthcare and enhancing decision-making, diagnostics, therapeutics, and resource use. In sub-Saharan Africa (SSA), where primary health care (PHC) systems face workforce shortages and high disease burdens, AI holds great potential. Yet, evidence on adoption remains fragmented and underexplored. This study identifies key factors influencing AI uptake and emerging best practices in PHC across SSA.

Methodology:

A literature review was conducted to examine the key enablers and barriers to AI integration in PHC across SSA and to analyse emerging best practices. Both peer-reviewed and grey literature published between January 2015 and June 2025 were included. A structured search strategy was applied across major databases and institutional sources. Findings were thematically analysed using the Non-Adoption, Abandonment, Scale-up, Spread, and Sustainability (NASSS) framework.

Results:

Findings revealed a growing number of AI applications in PHC across SSA, including diagnostic support, imaging, health education, screening, and administrative support. However, implementation is often limited to pilot projects. Barriers include infrastructure gaps, a lack of regulatory clarity, insufficient training, and data limitations. Enablers included government buy-in, inclusive design processes, investment, public-private partnerships, and capacity building. Emerging best practices include co-creation, interpretability/explainability, language inclusion, human-in-the-loop approach, offline AI tools, and federated learning.

Conclusion:

While AI offers real opportunities to enhance PHC services in SSA, adoption remains uneven. Stakeholder involvement, co-designing with users, capacity building, government ownership, and sustained investment are critical. Moreover, developing AI for health policies, strengthening regulatory frameworks, and ensuring ethical safeguards can not be overemphasized.

Keywords: Artificial Intelligence (AI), Adoption, Primary Health Care (PHC), Sub-Saharan Africa (SSA), Low and Middle Income Countries (LMICs), and Machine Learning (ML).

Word Count: 11,766 words

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List of Abbreviations

4IR = Fourth Industrial Revolution

AFP = Acute Flaccid Paralysis

AI = Artificial Intelligence

AI4D = AI for Development Africa

AUROC = Area Under the Receiver Operator Characteristic Curve

CAD4TB = Computer-Aided Detection chest X-ray tool for TB screening

CBE = Clinical Breast Exam

CDSS = Clinical Decision Support System

CEIMA = Center of Expertise in Montreal on AI

CHWs = Community Health Workers

CT = Computed Tomography

DL = Deep Learning

EHR/EMR = Electronic Health Record / Electronic Medical Record

HCWs = Health Care Workers

IRDC = Canada's International Development Research Centre

LLM = Large Language Models

ML = Machine Learning

MMR = Maternal Mortality Ratio

MRI = Magnetic Resonance Imaging

NASSS = Non-Adoption, Abandonment, Scale-up, Spread, and Sustainability

PHC = Primary Healthcare

PPP = Public-Private Partnership

SDG = Sustainable Development Goals

SSA = Sub-Saharan Africa

TB = Tuberculosis

UHC = Universal Health Coverage

WHO = World Health Organisation

Key Terms

- **Primary Health Care (PHC)**: "PHC is essential health care based on practical, scientifically sound, and socially acceptable methods and technology made universally accessible to individuals and families in the community through their full participation and at a cost that the community and country can afford to maintain at every stage of their development in the spirit of self-reliance and self-determination"(1).

- **Artificial Intelligence (AI)**: In healthcare, AI refers to the use of computational methods such as machine learning, natural language processing, and predictive analytics to interpret complex data, automate routine processes, and support decision-making in both clinical and operational contexts(2).

- **AI Adoption: "**AI adoption refers to the process by which organizations integrate artificial intelligence technologies into their operations, workflows, and decision-making processes.''(3).

- **Machine Learning (ML): "**Machine learning is a subset of Artificial Intelligence that enables a system to autonomously learn and improve using neural networks and deep learning, without being explicitly programmed, by feeding it large amounts of data."(4).

Introduction

"We should therefore move quickly to embrace AI and make it work for us."

Paul Kagame, President of Rwanda (Transform Africa Summit, 2023)

But should we? Or can we?

My name is Filmon Yohannes, a medical doctor from Eritrea with over five years of clinical and leadership experience across Eritrea, South Sudan, and Uganda. Working in underserved and overstretched health systems has shown me the daily struggles of frontline health workers, especially in rural primary care. From remote clinics without electricity to urban facilities overwhelmed by patient loads, I have seen how deeply health system gaps affect both access and quality of care. In these contexts, healthcare workers often operate under severe constraints, with limited diagnostics, delayed decision-making, and a constant struggle to deliver equitable services to communities that need them most.

These experiences sparked my interest in exploring new ways to strengthen PHC, particularly through the use of technology. Among the many digital innovations being discussed, artificial intelligence (AI) stands out as one with real promise to support frontline workers, improve diagnostics, streamline workflows, and extend care to underserved areas. However, I also recognize that AI is not a magic solution. Its success depends on how well it is understood, adopted, and adapted to the realities of our health systems.

This thesis focuses on the adoption of AI into Primary Health Care (PHC) systems in Sub-Saharan Africa (SSA). It aims to analyze factors that influence AI adoption and identify scalable solutions that could guide more effective and ethical implementation. I chose this topic because I believe AI, when developed and applied responsibly, has the potential to bridge critical service gaps and help build more resilient, people-centered health systems. Through this work, I hope to contribute evidence that supports policy, informs practice, and helps move the region toward stronger PHC and more inclusive digital health futures.

Chapter 1. Background

1.1. Introduction to Artificial Intelligence (AI)

Artificial Intelligence (AI) is transforming healthcare services around the globe by improving service delivery, personalized treatment, screening, diagnostic imaging, and enabling early disease detection, among others(5). Machine Learning (ML), a subfield of AI (**figure 1**) that requires a high-quality representative large data set for development, can analyze electronic health records (EHRs) and other patient data to help healthcare providers in clinical decision-making, diagnosis, or disease risk prediction(6). Deep Learning (DL), a more specialized branch of ML (**figure 1**) that is trained on high-quality annotated (labelled) large data sets, is proving invaluable in medical imaging, such as breast cancer detection and TB screening(7). Large Language Models (LLMs), a subtype of DL models, are trained on immense amounts of data (text, audio, or image) and understand, generate, and process human-like language(8). They are increasingly being deployed for clinical decision support, patient education (chatbots), treatment planning, and medical diagnosis, among others(8).

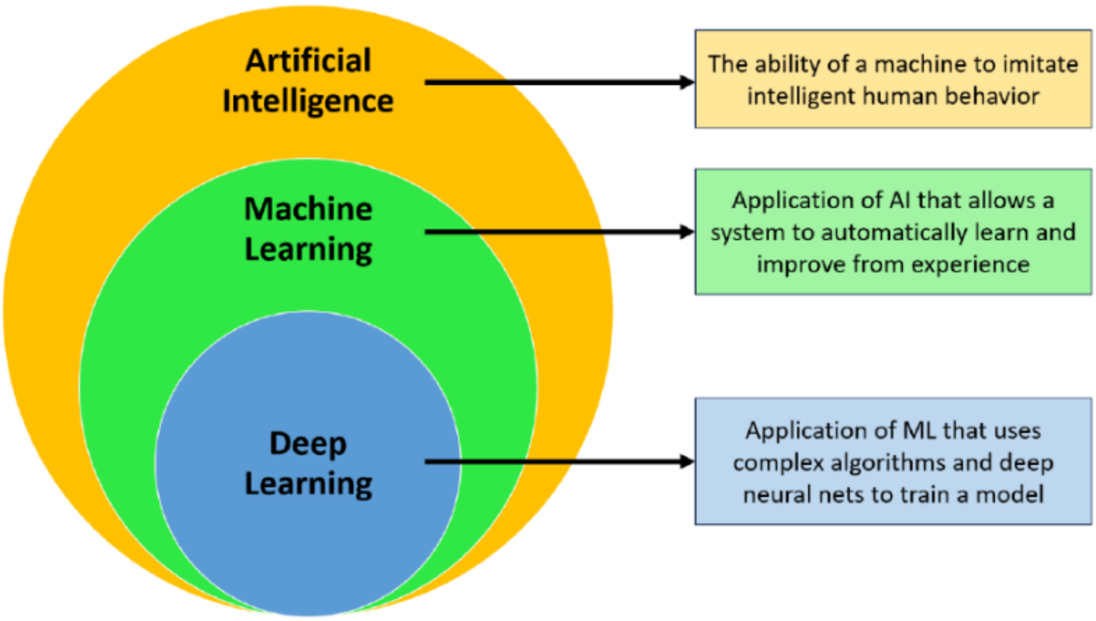

Figure 1: Relationship between AI, ML, and DL (2023)(9)

1.2. Sub-Saharan Africa Context

Sub-Saharan Africa (SSA) is a vast and diverse region consisting of 49 countries (**figure 2**), each with unique demographic and economic conditions(10). The total population is about 1.26 billion, roughly 16% of the world's population, based on estimates from 2024(11). Although urbanization is progressing steadily, with 45% of people living in cities, a significant majority (55%) still reside in rural areas and face healthcare access challenges(12). Many SSA countries struggle with heavy debt burdens, and more than half of those eligible for International Development Association support are either at high risk or already experiencing debt distress(13). The poverty rate is projected to reach its peak at 43.9% in 2025, using the international poverty line of $2.15/person/day (2017 PPP)(13). The adult literacy rate in SSA was approximately 68.2% in 2023, indicating that about one in three individuals aged 15 and above cannot read or write(14). In SSA, average life expectancy at birth in 2021 was 66 years, eight years below the global average of 74 years, while health expenditure was a mere $92 per person, about one-fifth of the spending in the next lowest region, the Middle East and North Africa ($379)(15).

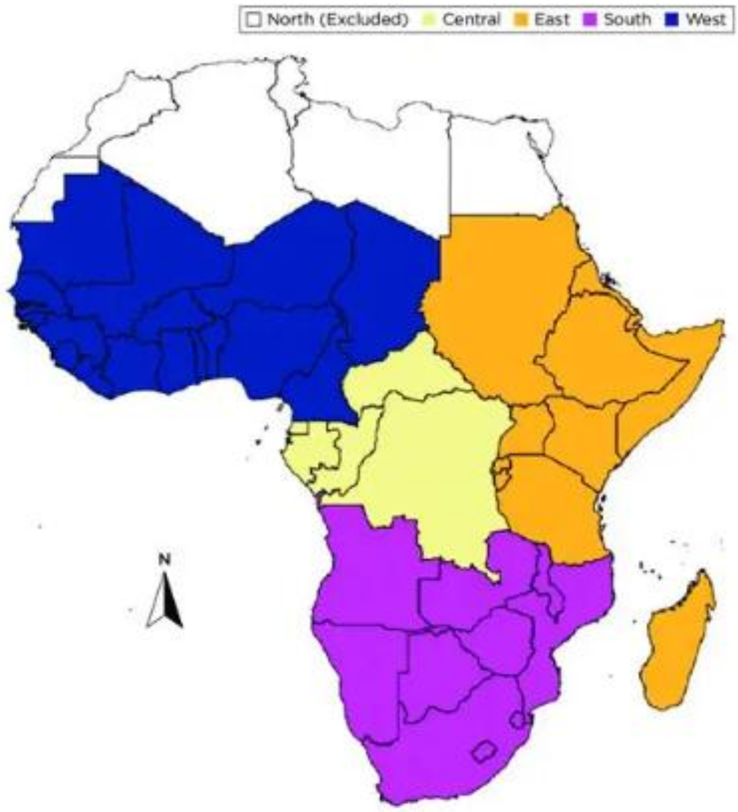

Figure 2: Map of Sub-Saharan Africa (2021)(16)

1.3. Healthcare Infrastructure and Disease Burden in SSA

SSA faces a high burden of infectious diseases, with HIV/AIDS, tuberculosis (TB), and malaria collectively claiming approximately 3 million lives each year(17). It has the highest under-5 mortality rate in the world, which was approximately 72 deaths per 1,000 live births in 2022(18). Moreover, the maternal mortality ratio (MMR) is alarmingly high at 545 maternal deaths per 100,000 live births in 2020, contributing to 70 % of global maternal deaths(19). The region is facing a rise in non-communicable diseases, particularly stroke, depression, diabetes, and ischemic heart disease(20). And all SSA countries, except Seychelles, Namibia, Mauritius, and South Africa, have a severe shortage (much lower than the WHO recommendation of 4.45 physicians, nurses, and midwives per 1000 population) of healthcare workers (HCW)(21).

In this context, Primary Health Care (PHC) serves as the foundational level of care and the first point of contact for most patients(22). PHC plays a vital role by providing essential services such as disease prevention, health promotion, and basic treatment(22). Despite its foundational role, PHC continues to face several challenges. First, there is a disproportionately high burden of communicable diseases in SSA, along with a rising prevalence of non-communicable diseases(23). Second, there is a severe shortage of trained healthcare professionals, which affects service delivery and the quality of care(24). Third, infrastructure limitations, including inadequate facilities and technology, also hinder the delivery of comprehensive PHC services(25). Fourth, insufficient government investment and poor health system financing impede the ability to meet healthcare demands, especially during crises like the COVID-19 pandemic(23,26).

1.3 Policy Landscape and Digital Health Initiatives in SSA

There are digital initiatives taken to tackle the challenges in the region, among which is the African Union's Digital Transformation Strategy for Africa (2020–2030) that highlights digital health as a key sector to drive the continent's socio-economic transformation and integration(27). As of 2024, 34 African countries had identified national eHealth strategies; however, only 16 had updated to cover 2023 or beyond(28). Among Africa's 54 nations, 41 have established national digital health strategies and implementation plans, with digital health technologies being applied in diverse ways(29). In 2024, the African Union High-Level Emerging Technologies Committee launched the Continental AI Strategy as a strategic blueprint for the continent's AI strategy with an implementation road map (2025 – 2030)(30). This roadmap emphasizes human capital development, AI infrastructure, regulatory and ethical governance, economic growth, and investment(31).

1.4 AI Applications in SSA

Currently, AI is being applied in analyzing medical images, predicting disease risk, providing health education, guiding public health interventions, and resource planning(32). In Kenya, a Computer-Aided Detection chest X-ray tool for TB screening (CAD4TB) has been deployed to automate and standardize the interpretation of chest X-rays, and it has significantly improved pulmonary TB detection(33). In Nigeria, an AI-powered health chatbot (AwaDoc) accessible via WhatsApp is providing health education and support for childhood immunisation programmes(34). An AI tool launched in Ghana in 2023 utilizes Google Maps' traffic prediction technology to help estimate the time it takes to reach emergency obstetric care. By offering real-time insights, it supports better planning and ensures that first responders can be positioned where women face the longest travel times to life-saving care(35). Despite such promising developments, the adoption of AI technologies into PHC systems in SSA remains sporadic and uneven(36).

Chapter 2. Problem Statement and Justification

Many countries in SSA face persistent shortages of healthcare workers, limited access to essential services, and overburdened systems, particularly at the PHC level, where the majority of people seek care(21,24). AI has the potential to deliver substantial value in PHC in SSA by enhancing productivity, improving diagnostic accuracy, providing Clinical decision support, providing health education, enhancing EHR management, and enabling remote care, among others(37). Specific applications and initial successes are already emerging in the healthcare system across the region. In South Africa, for instance, AI-driven tuberculosis detection has demonstrated strong performance in case identification, showing both high sensitivity and specificity(38). Similarly, in Zambia, an AI-based outreach screening programme for diabetic retinopathy has achieved a high sensitivity rate (92%) for identifying referable retinopathy, comparable to human graders(39). In Nigeria, a startup has developed an AI tool that accurately detects birth asphyxia by analysing newborns' cries, offering a novel diagnostic solution in low-resource settings(40).

Despite these promising developments, AI adoption in SSA's PHC remains limited. Real-world implementation depends on understanding the key drivers that influence uptake(41). Without this, PHC systems risk inefficient use of AI, wasted investments, and deepening inequities in service delivery(42). Yet, there is a marked knowledge gap around what drives or impedes AI adoption, how to overcome context-specific challenges, and which strategies are effective for ethical and sustainable integration of AI in PHC in SSA(43). For example, Yousefi et al. conducted a systematic review of AI implementation in PHC, focusing on opportunities and challenges; however, only 2 of the 109 included studies were from Africa(43). If context-specific AI implementation evidence is not generated, opportunities to improve health outcomes, build stronger and more resilient systems, and use scarce resources efficiently may be lost. Moreover, the absence of clear, evidence-based implementation strategies hampers policy development and undermines large-scale technological uptake(42). Many AI systems are still trained on data from high-income countries, raising valid concerns about algorithmic bias and poor performance when applied to African populations(44). As the World Health Organization (WHO) stresses, digital health tools must be ethically sound, locally relevant, and co-created with the communities they aim to support(45).

A lack of synthesized, context-specific evidence also impedes progress. Many existing initiatives remain stuck in the pilot phase and fail to scale or integrate into routine practice(32,46). Furthermore, the absence of documented best practices and locally relevant implementation strategies hinders effective policymaking and limits opportunities for regional scale-up. Addressing this evidence gap is urgent, as appropriately deployed AI tools can improve health outcomes, increase efficiency, and support the broader goal of achieving Universal Health Coverage and Sustainable Development Goals(43,47). This thesis, therefore, aims to investigate the key factors that influence AI adoption in PHC across SSA and to identify emerging best practices that can inform policy, scale-up, and sustainable implementation. It seeks to answer the central research question: What are the key influencing factors (facilitators and barriers) for the adoption of AI in PHC in SSA, and what are the emerging best practices in the region?

To address this critical research question, it is essential to systematically explore how AI can be effectively and ethically integrated into PHC systems in SSA. This literature review is justified on several grounds:

- First, despite the rapid progress in global AI discussions, there is a lack of synthesized evidence regarding the adoption of AI in PHC within SSA. Most existing studies are either technically focused or focused on a specific health condition or application in the region. By concentrating on PHC in SSA, this study enables the synthesis of new insights and evidence from fragmented or isolated studies.
- Second, this study advances the broader goal of achieving UHC by helping develop more resilient, data-driven PHC systems. It provides practical insights that can guide researchers, policymakers, donors, and technology developers working to promote responsible AI use in health across the region.
- Third, gaining a better understanding of the enablers, barriers, and best practices for AI integration in PHC could lead to impactful improvements in implementation strategies. This can help maximize the return on digital health investments, prevent technology failures, and ensure that AI is used ethically and equitably to benefit the populations that need it most.

Chapter 3. Objectives

3.1 Main Objective

To explore the adoption of AI in primary healthcare (PHC) within sub-Saharan Africa (SSA) by analyzing key enablers and barriers, and identifying emerging best practices for effective integration.

3.2 Specific Objectives

To address the main objective, the literature review is structured around the following specific objectives:

- To identify and analyse the key enablers and barriers influencing the adoption of AI in PHC settings within SSA from technological, adopters, organizational, and wider system perspectives.
- To analyze and present emerging best practices (promising solutions) for the adoption of AI in PHC across the region, drawing on documented case studies, pilot projects, and policy initiatives.
- To make actionable recommendations to support stakeholders in overcoming barriers and leveraging enablers for sustainable AI integration in PHC systems in the region.

Chapter 4. Methodology

4.1 Study Design

Literature review has been used to investigate the adoption of AI technologies in PHC across SSA, focusing on key influencing factors (enablers and barriers) and emerging best practices. Both peer-reviewed and Gray literature have been included to provide a clear understanding of the issue.

4.2 Search Strategy

A comprehensive literature search was conducted using three major academic databases: PubMed, Scopus, and Google Scholar. Search strings were carefully developed and tailored to each platform. Moreover, grey literature was reviewed by searching institutional databases such as the WHO IRIS, the Artificial Intelligence for Development Africa (AI4D) Research Directory, and relevant NGOs. Snowballing techniques were also applied to the reference lists of included papers to ensure a more comprehensive and enriched review of the literature. The search strategy (see annex 1) combined key terms related to Artificial Intelligence (e.g., AI, machine learning, deep learning), Primary Health Care (e.g., PHC, Primary Care, rural health), the sub-Saharan African context (e.g., individual country names, sub-Saharan Africa), and Adoption (e.g., implementation, integration, barriers, facilitators, best practices).

4.3 Eligibility Criteria

Inclusion and exclusion criteria were designed to ensure that selected studies were relevant to both the setting (SSA) and the topic (AI in PHC).

Inclusion Criteria:

- Studies or papers that report on the application or implementation of AI tools in PHC settings within SSA, or that provide relevant insights applicable to PHC in SSA,
- Articles, publications, or reports published in peer-reviewed journals or credible institutional sources (e.g., WHO reports) between January 2015 and June 2025,
- Publications available in English, and
- Studies providing insights into implementation experiences, outcomes, challenges, or lessons learned.

Exclusion Criteria:

- Studies solely comparing algorithmic performance without addressing contextual, technological, or health system-level adoption factors,
- Studies published before January 2015,
- Protocols, opinion pieces, or editorial articles lacking empirical data, and
- Papers published in non-English languages.

4.4 Screening and Selection Process

All papers identified through the search were screened using the predefined inclusion and exclusion criteria. They were exported from PubMed, Scopus, and Google Scholar as CSV files and uploaded to Rayyan, a platform for screening papers, for duplicate detection and initial screening of titles and abstracts. Duplicates were identified and removed, after which the titles and abstracts of the remaining papers were screened against the eligibility criteria. Studies that did not meet the inclusion criteria were excluded. The remaining full texts were assessed for relevance based on the inclusion/exclusion criteria, leading to the final selection of papers. Relevant papers cited in the included papers were also snowballed and added to the final list based on the inclusion criteria. For grey literature, papers meeting the inclusion criteria were included and added to the final list continuously through searches of relevant websites and databases, as mentioned in the search strategy.

4.5 Data Extraction and Synthesis

A total of 94 papers have been included in this review from both peer-reviewed (72 papers) and grey literature sources (22 papers). All included papers were screened, and relevant findings extracted using the analytical framework (next section) to capture key elements, including: author(s), year, country, type of AI application, health system context, PHC setting, barriers and enablers to adoption, and promising/scalable solutions for AI adoption. Extracted data were synthesized thematically, with findings categorized using the selected theoretical framework. Zotero was used as a reference manager to manage citations, and Grammarly was used for grammar and spelling checks throughout this work.

4.6 Analytical Framework

To guide the analysis of this literature review, the **Non-Adoption, Abandonment, Scale-up, Spread, and Sustainability (NASSS)** framework (**figure 3**) developed by Greenhalgh et al. (2017) was employed(48). The NASSS framework was selected due to its demonstrated relevance in examining the multifaceted challenges of adopting complex technologies in healthcare systems. It has proven particularly useful for digital tools and AI applications in the healthcare sector. For instance, Alami et al. applied the NASSS framework to identify barriers and enablers of AI integration in Canadian healthcare organisations (49), while Abell et al. used it in a scoping review on the implementation of computerised clinical decision support systems (CDSS) in hospitals(50). The framework comprises seven interlinked domains: 1) the condition or illness, 2) the technology, 3) the value proposition, 4) the adopters, 5) the organisation, 6) the wider system, and 7) embedding and adaptation over time(48). These domains enable a holistic and systems-level understanding of implementation processes and outcomes. Moreover, the domains enable assessing the adoption of AI from the perspectives of the technology (AI), adopters, healthcare setting, and wider context, making it well-suited for the objectives of this review.

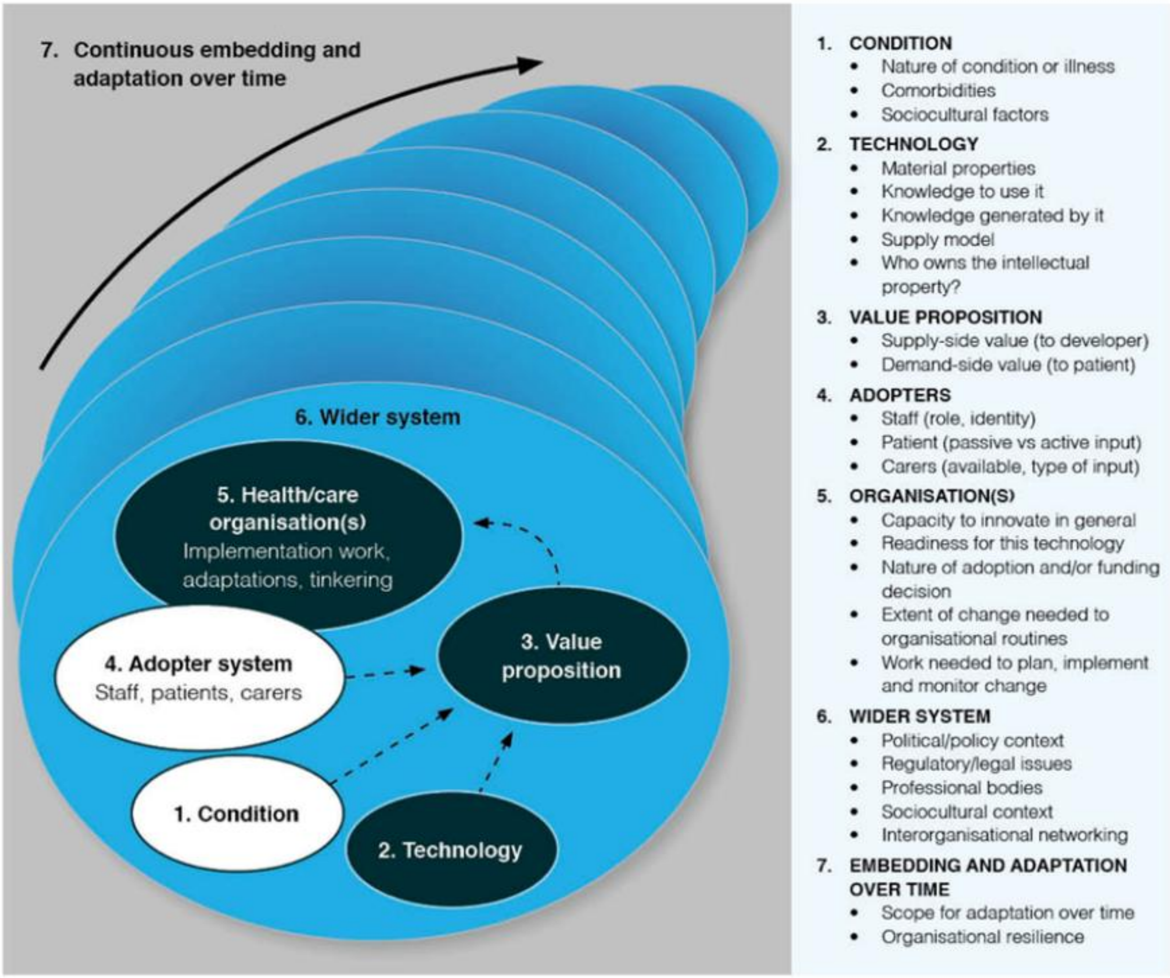

Figure 3: Non-Adoption, Abandonment, Scale-up, Spread, and Sustainability (NASSS) Framework(51)

For the specific aims and scope of this literature review, five domains of the NASSS framework have been explored: Technology (AI), the Value Proposition, Adopters, Organisation, and Wider System. The 'condition' domain has been left out as it pertains to illnesses or clinical conditions the technology is applied, and has been discussed in the background and problem statement. Moreover, its implications often manifest within other domains (e.g., value proposition or adopters), thus making a dedicated domain redundant for this analysis. The 'Embedding and Adaptation Over Time' domain was also excluded due to the focus of this review being limited to the initial adoption, scale-up, and spread of AI tools. The long-term, iterative embedding phase falls beyond the review's scope and timeframe. Yet, the sustainability of adopted AI tools has been discussed in this review, mainly in the wider system.

In the adopters' domain, the findings were inductively generated based on recurring patterns, issues, and concepts emerging from the reviewed literature. And a sub-section for ‘infrastructure’ has been added in the wider system, as it is not mentioned in the sub-sections of the framework, despite its importance. This thematic flexibility enabled the analysis to better reflect the specific contexts of SSA. This approach is consistent with precedent in the literature. For example, both Alami et al. and Abell et al., in their use of the NASSS framework to study adoption of AI and digital tools in healthcare, categorised findings by NASSS domains while allowing subthemes to emerge inductively from their data(49,50). Such methodological flexibility is well-supported when analysing complex sociotechnical systems.

4.6.1 Limitations of the Framework and Mitigations

The NASSS framework does not focus on any specific technology and requires the researcher to reflect on their particular application strategy(48). To address this, the application of the framework was tailored by mapping relevant AI interventions against each NASSS domain, ensuring that the analysis remained grounded in the specific context of AI adoption in PHC in SSA. The NASSS framework has been used as a guiding lens rather than a rigid tool, supporting thematic synthesis and interpretation.

Moreover, while the NASSS framework includes stakeholder perspectives, it does not explicitly address power dynamics or equity issues(48), an important limitation in SSA where health inequities and externally developed AI tools are common. To address this, the role of actors involved in the development and deployment of AI tools will be critically examined and relevant concerns highlighted.

4.7 Identification of Emerging Best Practices

Emerging best practices in this review were identified using the WHO Afro Region’s Guide for Documenting and Sharing “Best Practices” in Health Programmes(52). According to the guide, a practice must meet at least three core criteria: effectiveness, efficiency, and relevance, and one or more of the following: ethical soundness, sustainability, replicability, partnerships, or community involvement. Recognizing that many AI innovations are still evolving, practices included here were selected based on their demonstrated potential to produce meaningful results within resource-constrained settings and their relevance to strengthening AI in PHC across SSA.

Chapter 5: Results

Several facilitators, challenges, and promising solutions have emerged in the adoption of AI in PHC in SSA. They are presented below in five domains from the NASSS framework (Technology, Value Proposition, Adopters, Organisation, and Wider System) under relevant themes, and presented in table summaries at the end of the section (**Tables 1 and 2**).

5.1. Technology

This section examines the characteristics of AI technologies introduced in PHC settings across SSA, focusing on their technical robustness, usability, and fit within local contexts. It explores aspects such as functionality, data requirements, integration complexity, and potential for local adaptation.

5.1.1. Material (AI) Properties

5.1.1.A. Data Requirement for AI Model Development

AI applications depend heavily on high-quality, well-structured representative data for effective training, which is often lacking in low-resource settings such as SSA(44). Dataset size significantly influences the accuracy and reliability of AI models in healthcare, with larger datasets supporting better generalization and improved predictive performance across varied patient populations(53). In contrast, smaller datasets limit the model's ability to learn meaningful clinical patterns, often resulting in reduced accuracy and poor generalization. For instance, in Zanzibar, an ML model developed to predict delivery locations among pregnant women achieved an accuracy of 68%–77% on the test set because 14% of follow-up records were missing(54). Similar challenges have been reported elsewhere: in Kenya, Friedman et al. found ML models to be highly predictive for HIV screening, yet hindered by poor-quality and incomplete data(55). In Ethiopia, researchers developing a model to detect Acute Flaccid Paralysis (AFP) faced training difficulties due to poor image quality, an issue caused by limited technical expertise among community volunteers who captured the data(56).

The type of data also influences AI model feasibility and success. Imaging data, such as X-rays or radiology scans, is more structured and easier to annotate with clear labels, and as a result, AI adoption is generally more advanced in radiology(57). On the other hand, textual health data is unstructured, semantically complex, and less standardized, posing greater challenges for model development and often requiring much larger datasets and sophisticated preprocessing(58). For example, O'Donovan et al. developed 'CHWSupervisor' in Uganda, an open-access AI web application designed to support community health worker (CHW) supervision and communication, using 3429 digital supervisory exchanges, but the model couldn't perform beyond identifying gross themes(59).

5.1.1.B. Algorithmic Bias

Most AI models are developed in high-income countries, which poses a risk of bias when applied in a geographically or socio-demographically different context(60). Similarly, most LLMs are developed in the global north and pose the risk of reinforcing inequities through bias and/or hallucinations (Subtly wrong and ungrounded information)(61). Algorithmic bias is a challenge to AI integration in PHC in SSA, and can lead to inappropriate recommendations, such as unnecessary lab tests, incorrect diagnoses, or inadequate treatments, when AI is applied outside its original training context(44). In a Nigerian pilot study, McPeak et al. assessed an AI clinical decision support tool in primary care that assists frontline health workers in real-time. The AI tool frequently suggested contextually irrelevant tests (e.g., MRI, CT), reflecting biases from high-income country data(62). Moreover, the AI tool recommended more than routine laboratory tests repeatedly, many of which were unavailable in the setting(62). Another example is the DawaMom app developed in Zambia, which was designed to offer AI-powered maternal health support. Its algorithms rely heavily on an open-source data repository (Kaggle), which does not reflect local knowledge systems or traditional maternal care practices. This has led to unintended biases, such as poor cultural alignment, inaccessibility for users with low literacy, and limited relevance for women in rural communities, which risk reducing the app's effectiveness and adoption(63).

A critical enabler here is to develop and use locally available data to enable AI adoption in PHC in SSA, as demonstrated by the following examples(64,65). In Uganda, Nakasi et al. have created a locally annotated malaria image dataset of 1000 labeled thin blood smear images and 3000 thick blood smear images, which can be used to train malaria diagnostic AI models. The data set enables the development of malaria diagnostic AI models, although it might not be generalisable to other settings because over 95% of the images depict only the Plasmodium falciparum species and its trophozoite stage(65). Similarly, Turbe et al. have created a library of 11,374 annotated HIV RDT image datasets, which can be used to train AI models. They did this when they developed and deployed a DL model for HIV diagnosis as a mobile application in rural area in South Africa, which showed high performance(97.8% sensitivity and 100% specificity, with 98.8% accuracy) in classifying HIV lateral flow tests and outperformed visual interpretation of study participants (92.1%)(64).

5.1.1.C. Offline Functionality

Reliable internet connectivity is often a technical requirement for AI tools, especially those relying on cloud storage and real-time computing(66). For instance, Lee et al. were working on using a voice-based AI tool, using Amazon Alexa and ML to provide frontline health workers in Sierra Leone with health education and information(67). However, the tool requires stable Wi-Fi, which is difficult in the largely rural setting in Sierra Leone's Makeni Region, where only patchy 3G/4G mobile coverage was available, challenging the project(67).

To overcome such challenges, offline functionality (working without internet) has emerged as a critical enabler for AI adoption in low-resource PHC settings in SSA. In The Gambia, researchers transformed a pneumonia mortality risk ML model into an offline mobile triage tool using

Google's Progressive Web App (PWA) format(68). This allowed the AI-driven tool to run on any device, phone, tablet, or desktop, without internet access, making it suitable for frontline deployment in the context(68). Similarly, in Malawi, Taylor et al. developed IntelSurv, an offline mobile AI app that supports self-directed learning for CHWs by providing local health guideline answers and information on priority diseases(69). The app, which updates when the internet is available and maintains a feedback log for the Ministry of Health, was tested in two cities and received positive evaluations from healthcare workers(69).

Several other innovations highlight the value of **offline and low-resource functionality**:

- **Saytù Hemophilie Chatbot** in Senegal, developed with haemophilia patients through co-creation, runs on mobile devices without needing internet, allowing reliable self-learning for users in low-connectivity areas. More importantly, it provides educational information in French and Wolof (a local language), and it achieved high user satisfaction with an average System Usability Score of 81.7 (an excellent usability which indicates higher adoption)(70).
- **Ebola CARE** in Sierra Leone was developed as an offline clinical support app using local data and ensemble modelling techniques (using multiple models simultaneously). Despite a small training dataset, the app demonstrated strong offline utility, achieving an AUROC (an indicator for AI performance) of above 0.8 (71).

5.1.2. Knowledge Required to Use It

The use of AI systems in PHC requires a baseline of digital literacy and technical understanding, which is currently limited across many SSA settings. In Sub-Saharan Africa's PHC settings, a significant number of healthcare workers possess only basic digital skills, often limited to programs like Microsoft Word, which hampers the adoption of advanced AI-driven tools such as CDSS(72). In a study exploring the role of AI in enhancing EHR systems in Tanzania, many healthcare professionals recognized AI's potential to automate tasks, predict system failures, reduce medical errors, and flag high-risk patients; however, a general lack of familiarity with AI technology was cited as a major challenge to effective implementation(73). Similarly, in a study from Ethiopia, although over half of the health professionals (n = 404) expressed familiarity with basic AI principles and held positive attitudes toward its potential to enhance diagnostics and patient care, only about one-third had received formal training or participated in relevant workshops(74).

Here, practical, task-specific training can bridge knowledge gaps and enable frontline staff to effectively use AI tools(75). In a mixed-methods study on AI deployment in Africa involving experts (in health, policy, and AI) and general populations, the experts recommended integrating digital health and AI education into healthcare curricula and professional training programs to build safe and effective use of AI(75). In Zambia, a mobile diabetic retinopathy screening program integrated AI into community outreach, using trained nurses and imaging technicians, rather than specialists, to capture retinal images for AI analysis. The AI achieved expert-level diagnostic accuracy (AUC = 0.973), demonstrating how targeted training enables task-shifting in resource-limited settings(39).

5.1.3. Knowledge Generated by It

AI tools deployed in SSA have shown potential to generate clinically relevant insights that enhance decision-making in PHC. For instance, an AI tool in Tanzania forecasts bi-weekly facility vaccine utilisation rate with a prediction accuracy 18-fold compared to traditional methods(76). In South Africa, a Breast AI examination tool demonstrated higher sensitivity than the Clinical Breast Exam (CBE) by detecting four cases that were missed, improving diagnostic accuracy and enabling risk-based referrals(77). Similarly, PROMPTS (AI chatbot) in Kenya has empowered millions of mothers to seek timely care, significantly improving antenatal visits, high-risk pregnancy management, postpartum family planning, and exclusive breastfeeding rates by providing AI-powered clinical information(78).

Moreover, as endorsed by the WHO, AI technologies should be designed to be transparent and explainable, ensuring that all stakeholders, including developers, clinicians, patients, and regulators, can understand how the system works, how decisions are made, and how it should be used or governed(42). Developing explainable AI (XAI) is a best practice in healthcare AI, as it enhances transparency, trust, and ethical compliance by making medical decisions more interpretable and reliable for both clinicians and patients(79). An example of this is a Vaccine Forecasting AI tool in Tanzania mentioned earlier in this section. It was developed in an interpretable way using local health facility data, and enables workers to get insights and act on the factors that influence vaccine utilisation(76). Similarly, in Kenya, interpretable ML models were applied to malaria risk prediction, offering transparent insights into key clinical and environmental risk factors(80).

5.1.4. Supply Model, Cost, and Ownership

Most AI models are developed in the global north and carry the risk of bias (**section 5.1.1.B**) if directly applied in different contexts(60,61). The initial investment required for AI infrastructure, software, and training can be prohibitive for many PHC settings in SSA(81). Beyond these upfront costs, the long-term sustainability of AI solutions, such as maintenance, technical support, and software updates, poses additional financial challenges(81). The cost of implementing AI in healthcare is highly variable and influenced by multiple factors, including model complexity, infrastructure needs, integration requirements, and the availability of clean, labeled data, ranging from $10,000 for simple applications to well over $500,000 for advanced, custom-built systems(82).

These substantial financial demands, combined with high expertise requirements and ongoing operational costs, hinder AI adoption in PHC across SSA(72). Ashinze et al. highlighted the promising applications of AI in managing cardiovascular diseases, such as early diagnosis, medication reminders, and remote follow-ups, but noted the high cost of AI development and that funding tends to prioritise infectious diseases like malaria in Africa(83). The AI ecosystem in SSA is heavily donor-dependent, with limited public sector investment(41). Many of the AI projects are funded by donors such as the Bill and Melinda Gates Foundation (BMGF), UK International Development, Canada's International Development Research Centre (IDRC), Swedish International Development Cooperation Agency (Sida), and Big Tech companies, among others(41). Moreover, because large technology firms and commercial actors often bear the costs of development and data acquisition, they tend to retain ownership or control over datasets, resulting in high-cost licensing (IP ownership) and restricted access, reinforcing power imbalances and limiting equitable usage(84).

5.2. The Value Proposition

5.2.1. Demand Side Value (clinicians, patients, healthcare facilities)

Demonstrated utility is a key factor influencing the routine integration of AI tools in PHC. For example, for 'CHWSupervisor', discussed in **section 5.1.1.A** above, its suboptimal predictive accuracy and inability to match human reliability limited its usefulness for supervisory decision-making(59). Similarly, a South African ML model intended to predict rural health worker retention achieved only 47% accuracy, driven by insufficient and unrepresentative training data, limiting its real-world implementation(85). Thus, when an AI tool is not delivering the expected utility, it won't be adopted. In contrast, evidence of clear clinical utility can serve as a strong enabler of AI adoption. In Nigeria, an AI-based medical diagnostic support (the Febra Diagnostica app) developed using locally sourced data and expert input from tropical medicine specialists, demonstrated strong clinical utility by supporting the diagnosis of 11 regionally prevalent febrile illnesses, including malaria, TB, HIV, typhoid, and dengue, among others. Its contextual relevance, diagnostic range, and secure, user-friendly design align well with frontline clinical needs, enabling its deployment in PHC facilities(86). In a cross-sectional study conducted in South Africa and Lesotho, Nzimande et al. evaluated two versions of CAD4TB (V6 and V7) in a TB screening program, which demonstrated high clinical utility, with V7 showing improved diagnostic accuracy over its predecessor(38). The AUROC (an indicator for performance) was 0.833 (95 % CI 0.808–0.859) for V6 and 0.865 (95 % CI 0.842–0.889) for V7(38). This CAD4TB has met WHO performance standards, and it has been recommended by WHO for routine TB screening for people aged 15 and above(87). This illustrates how strong clinical performance and value proposition can facilitate AI adoption in PHC.

5.2.2. Supply Side Value (including economic return)

AI holds significant economic promise for developing countries through potential cost savings, improved quality of care, and enhanced patient safety(88). Despite limited definitive evidence on the cost-effectiveness of AI in healthcare settings, the demonstrated gains in operational efficiency and service delivery indicate that AI could lead to substantial financial and systemic benefits when effectively implemented(88). For instance, in Kenya, an AI CDSS Copilot implemented by Penda Health in Primary Care demonstrated notable cost-saving potential by reducing diagnostic errors by 16% and treatment errors by 13% across 39,849 patient visits, translating into thousands of averted errors annually and fewer costly follow-up visits or inappropriate treatments(89). In Rwanda, an AI-powered decision support tool using Kinyarwanda-trained language models significantly improved diagnostic accuracy by frontline health workers, from 8% to 71%, which reduces healthcare costs by preventing misdiagnoses and unnecessary referrals(90). AI can also help prevent disease progression and improve health outcomes while lowering long-term healthcare costs through early disease detection and prediction(91). For instance, Omdena's AI-driven app in Liberia forecasts malaria outbreaks, allowing health professionals to act in advance, especially to protect vulnerable populations like children and pregnant women(91). Moreover, AI-powered telemedicine can reduce travel costs for patients and providers, especially in rural or underserved areas, and potentially lower infrastructure costs for physical clinics(92). These finding shows that AI demonstrates strong potential to enhance economic efficiency in PHC, despite limited conclusive cost-effectiveness data.

5.3. Adopters System

This section focuses on the readiness and response of key adopters, including health workers, patients, and the community, toward AI integration. It highlights variations in digital literacy, perceptions of clinical autonomy, and attitudes towards AI and trust in algorithmic decision-making.

5.3.1. Trust and Confidence of Adopters (HCWs and Patients) in AI

Privacy, data protection, and trust are recurring concerns in the integration of AI in PHC in SSA. In Western Cameroon, a study on healthcare workers' (HCWs) perspectives toward an AI-based cervical cancer screening tool revealed a positive attitude toward its diagnostic accuracy and the reassurance it provided to patients(93). However, concerns about data privacy, particularly the unauthorized sharing of mobile-phone-captured images, posed significant barriers to trust and adoption(93). Similar privacy-related concerns were observed in another study that explored the perspectives of women on an AI cervical cancer screening tool using mobile phone captured images of the cervix. Some women who participated in the study feared that their images might be shared on social media(94). Moreover, in the two studies above, participants expressed concern about HCWs being overly reliant on AI and losing their skills (de-skilling)(93,94). In the mixed-methods study mentioned in **section 5.1.2**, while a majority of the general population expressed strong trust in AI/ML for health (74–78%) and believed it could empower health in their countries (72%) with significant benefits (98%), many voiced concerns (89%), mainly about fairness and accuracy(75).

In addition to this, there is also concern or fear of job loss with the integration of AI. In a cross-sectional study of medical imaging professionals, 61.3% (n=625) expressed concern that AI could replace their roles rather than simply supporting them(95). A similar study in Ghana by Botwe et al. found that although radiographers were generally optimistic about AI's potential in medical imaging, key barriers included concerns over AI-related errors (83.4%), ethical data use (38.4%), and job security (23.2%)(96).

Despite these challenges, some studies identified factors that could enhance trust in AI systems. For example, in a study in Ghana, transparency and accountability in AI systems were rated as highly important (mean score: 4.27/5) in enhancing HCWs' trust in AI systems(97). The study participants demanded safeguards such as regulatory oversight (91.7%) and embedded consent features (60.8%), reflecting a widespread concern for privacy and ethical use of health data (mean privacy score: 3.58/5)(97). The research also underscored the importance of clear communication about how these systems are developed and function to enable HCWs to maintain oversight and confidence in AI-driven decisions(97). And over 50% of respondents stressed the need for AI developers to prioritize fairness and regular bias assessments to ensure equitable outcomes(97). An emerging best practice here is co-creation with users, which fosters trust, usability, and user engagement in PHC contexts, as demonstrated in **section 5.1.1.C** with the Satyu Hemophilie mobile application in Senegal(70). Moreover, preserving human agency and involving shared decision-making in the implementation of AI in SSA healthcare is crucial for the AI to be ethically acceptable and better received by both clinicians and patients(98).

5.3.2. Knowledge and Awareness of Adopters (HCWs, Patients, or Community)

Limited awareness and understanding of AI among healthcare workers remain a key barrier to its adoption in PHC settings. A study from Tanzania on the role of AI in enhancing EHR systems in PHC reported a lack of familiarity with AI technology among HCWs as a major challenge(73). In a study from Ghana, low AI literacy was common among HCWs, with 82.8% of participants reporting limited knowledge about AI(96). Similarly, in a study involving the general population from several African countries, most of the participants had some familiarity with AI, comprising regular users (11%), those who had read and used it (43%), those moderately familiar (31%), conceptually aware (14%), and unfamiliar (2%)(75). Apart from this, socio-cultural beliefs and misinformation can also hinder the adoption of AI. Ephraim et al. found that digital illiteracy, along with misconceptions, such as fears that AI threatens human existence or lacks empathy, creates confusion and resistance, often from cultural narratives or misinformation(99).

While healthcare providers often express positive attitudes toward AI and digital tools, a lack of training and local expertise limits their ability to utilize these technologies effectively(96). For example, in a study conducted in Tanzania, some healthcare practitioners reported having heard of AI but lacked a clear understanding of what it entails(68). Therefore, empowering healthcare workers with a solid understanding of AI's capabilities and limitations is critical to ensuring both safe use and long-term trust in the technology(99). To address these challenges, capacity-building efforts, either by integrating AI education into health training curricula or offering continuous professional development opportunities, are crucial(100).

5.3.3. Cultural and Linguistic Alignment with Adopter Needs

Despite increasing interest in AI for health, persistent gaps in linguistic inclusivity, particularly the underrepresentation of widely spoken African languages, highlight the critical need for language-inclusive design to ensure AI tools are accessible, trusted, and effective for sub-Saharan African Adopters(101). The following locally grounded, language-inclusive solutions in

SSA demonstrate how user-centeredness and cultural responsiveness enhance the practical utility of AI in primary healthcare:

- **MAVSCOT in South Africa** is an AI–based HIV diagnostic system designed with a user-centered interface to support multilingual communication (English, Afrikaans, Zulu, and Xhosa) between healthcare workers and rural patients. It enhances diagnostic utility by aligning clinical information delivery with local language and cultural contexts(102).
- **Digital Umuganda in Rwanda** developed voice and text datasets in Kinyarwanda and embedded them into AI tools that interact with LLMs. This locally driven translation system improves information access by enabling users to ask questions in Kinyarwanda and receive AI-generated responses, overcoming linguistic and technological barriers(103).
- **PROMPTS in Kenya** is a Swahili-speaking maternal health chatbot (mentioned in Section 5.1.3) that answers queries from expectant and new mothers and flags high-risk cases based on chat content for timely follow-up by help desk agents. Reaching nearly 3 million users, its culturally responsive and user-centred design has enabled scale-up and government-backed expansion into Ghana and Eswatini, demonstrating strong clinical utility and adaptability across diverse contexts(78).
- In Mali, a **human-in-the-loop AI tool** was developed to translate COVID-19 health education materials into Bambara (local language) using crowdsourced Bambara-French/English translations. Despite challenges related to data scarcity and cultural-linguistic alignment, the tool achieved modest translation performance. This initiative highlights the value of local engagement and tailored AI development in improving access to public health information for marginalized linguistic communities(104).

5.4. Organisation (PHC System)

This domain assesses the capacity of the PHC system to adopt and sustain AI tools. It covers internal readiness for change, data infrastructure, leadership engagement, funding mechanisms, and organizational workflow/culture that either enable or obstruct effective implementation.

5.4.1. Capacity and Readiness for AI

AI systems require large volumes of high-quality, locally relevant data to function effectively(44). In the SSA PHC system, however, health data are often fragmented and/or stored in incompatible digital formats, making both collection and integration challenging(105). Although healthcare systems in SSA generate substantial data, much of it remains underutilized due to limited infrastructure for storage, management, and analysis(32). The sparse adoption of EHR and weak digital infrastructure means that most health records are still paper-based, hindering the availability of structured, local datasets for training AI tools(105). As a result, many AI models developed globally are trained on non-representative data, which might result in algorithmic bias(44).

Moreover, the lack of clear internal policies and guidelines around AI implementation, data privacy, and ethical use is a challenge(44). This is particularly concerning given that many AI tools in African healthcare rely on sensitive patient information, such as biometrics and/or medical records, yet operate within weak policy frameworks and opaque data practices, increasing the risk of misuse and legal conflict(72). Poor data governance can also erode public trust if sensitive information is mishandled, and unrepresentative or low-quality data can result in biased algorithms(100). Donkor et al. emphasize the importance of strong data governance and explicit patient consent mechanisms as essential safeguards against the unauthorized use of health data in AI systems(97).

Apart from this, interoperability is essential for integrating AI into PHC, preventing fragmentation by enabling seamless data exchange across systems. Hence, adopting open standards (publicly available and interoperable) is crucial to enhance Health Information Systems (HIS) and ensure innovations are scalable and adaptable to diverse health contexts(106). Fragmented and non-interoperable HIS create significant barriers to implementing AI-driven tools in routine workflows, underlining the importance of harmonising digital platforms such as OpenMRS and DHIS2 to enable seamless integration into frontline PHC practice(107).

The PHC system in SSA also faces significant infrastructure challenges (see details in **section 5.5.6.**), including a shortage of healthcare facilities and medical equipment, factors that directly constrain quality care delivery and the adoption of technologies like AI(41). Many health facilities, especially in rural areas, experience frequent power outages and limited or no internet access, making it difficult to deploy and sustain AI systems(99). For instance, Umar et al. reported that the absence of internet and digital devices significantly impedes the implementation of advanced technologies, including AI, in rural PHCs in Nigeria(108).

Furthermore, the effective integration of AI relies heavily on the technical capacity of the staff; however, many facilities lack personnel with the digital expertise to operate, interpret, and manage AI systems(99). The workforce faces challenges in terms of unequal access to digital tools (smartphones over computers), insufficient ICT training, and limited digital skills(109). A study on workforce digital health readiness in South Africa has revealed gaps in workforce capacity, with less than half of the respondents having experience with digital solutions before (45%), and only a similar share felt ready (44%) or comfortable (45%) using them(110). Mwogosi et al. identified inadequate training as a key barrier to AI and Internet of Things (IoT) integration in Tanzanian PHC, emphasizing the need for targeted capacity-building initiatives(111).

5.4.2. Funding decision

Limited funding remains one of the most significant barriers to the adoption of AI and other digital health technologies across SSA(32). In many countries, investment in AI is minimal, leaving digital health systems heavily reliant on donor funding(44). Moreover, there is a limited fund for AI research due to the prioritization of prevalent diseases or programmes(83). Research from South Africa highlighted the great potential of generative AI in healthcare in South Africa, but identified limited funding as a major barrier to implementation(112). As already pointed out (section 5.1.4), most of the AI projects in SSA are funded by international organizations or foreign governments, with limited local government funding (41). The ‘State of AI in Healthcare in SSA’ report (2024), published by the International Center of Expertise in Montreal on AI (CEIMIA) with support from IDRC, emphasises the need to invest in local ecosystems to unlock AI’s potential in SSA. It underscores that robust data infrastructure, coherent national AI strategies, and support for local innovation hubs are essential for attracting sustainable investment(41). Furthermore, the report calls for strategic government-led funding and coordinated donor engagement to ensure AI investments align with health system priorities and drive meaningful, long-term impact(41).

5.4.3. Extent of Change to Organisational Routine

The extent of change needed to the PHC workflow routine is an important factor in the integration of AI. Sukums et al. showed that CDSS tools are most likely to be adopted when integrated smoothly into existing maternal care workflows in their implementation of CDSS for antepartum and intrapartum care in rural PHC in Tanzania and Ghana(113). A mixed-method study on the integration of CDSS for child health in PHC in South Africa had limited uptake because it disrupted established maternal and child health workflows, showing how poor integration into daily routines significantly undermines CDSS and AI adoption(114).

In general, successful AI integration into healthcare workflows requires significant adaptation of infrastructure and organizational systems, pilot testing, ongoing training, and post-implementation support to ensure safety, compliance, and sustainability(115).

5.4.4. Work Needed to Plan and Implement

An OECD survey, which included countries such as Nigeria, Senegal, Somalia, and Rwanda, identified "insufficient digital literacy" among both health workers and decision-makers as a moderate to major barrier to AI adoption in healthcare(116). There was similar concern in a multi-country stakeholder workshop in Africa, where participants emphasized the urgent need for capacity building, ongoing training, and organizational preparedness to support AI integration into healthcare systems(117). Key recommendations included the establishment of regular training platforms, experience-sharing forums, and the development of national AI roadmaps(117). Similarly, medical imaging professionals in Ghana highlighted the importance of education programs to raise AI literacy and facilitate effective implementation(97). As such, embedding training and upskilling into medical curricula and continuous professional development programs is critical to enabling AI adoption(100).

Beyond technical skills, strong organizational leadership is also essential. Successful adoption requires early engagement, strategic planning, and leadership buy-in to ensure AI initiatives align with clinical priorities(115). However, a South African study has revealed gaps in leadership support (only 48% of managers discussed practical implementation) and cultural adaptation (52% of workers adapt work routines to digital tools, and 45% discussed workflow changes), which are critical barriers(110). A qualitative study of health-care leaders in Uganda found that effective leadership, especially in change management, strategic alignment, and stakeholder engagement, is critical for successful AI adoption(118). Empowering local stakeholders through inclusive leadership, sustained training on AI, and context-specific implementation are required to foster the development of responsible, equitable, and scalable AI systems in these settings(119). As Ndembi et al. noted, successful AI integration requires a thorough needs assessment, defining clear objectives, inclusive stakeholder engagement, comprehensive training during implementation, and continuous monitoring and evaluation(66).

5.5. Wider System

This section analyses broader systemic factors for AI adoption, including political commitment, regulatory landscapes, the role of professional bodies, socio-cultural norms, inter-organisational collaboration, and infrastructure (summary in **table 2** below).

5.5.1. Political Context and Government Leadership

Several SSA countries have shown increasing political will and institutional commitment to advancing AI in health through national strategies, legal frameworks, and regulatory reforms(117). Governments in South Africa, Rwanda, and Kenya, for example, have initiated public sector reforms, established national AI task forces, and created centres dedicated to AI innovation(117). According to the Science for Africa Foundation report, several countries in SSA, including Kenya, South Africa, Nigeria, Ghana, Mauritius, Malawi, Ethiopia, and Rwanda, have launched or are actively pursuing national AI programs and strategies(120).

At the 2018 Transform Africa Summit, strong government leadership was highlighted as essential for scaling digital health in SSA, stressing the need for national strategies and coordinated implementation(121). Evidence from country and regional initiatives shows that government ownership leads to more integrated, cost-effective, and contextually relevant digital health solutions (including AI)(121). Similarly, the 2021 AI for Health virtual workshop reinforced that national coordination, ownership, and strategic readiness are key to sustainably integrating AI into health systems in Africa(117). Rwanda has developed its national AI policy, and its strategy prioritizes ethical deployment, public sector transformation (including health), data protection, and capacity building, fostering a multisectoral model for responsible AI adoption through strengthened governance, infrastructure, and skills development(122). In Ethiopia, strong leadership from the Ministry of Health facilitated a successful partnership with Last Mile Health and IDinsight to co-develop HEP Assist, an AI-powered clinical decision support tool for community health workers(123). This initiative showcases how government-led collaboration with technical partners can foster AI innovation in primary care, empowering frontline workers to better manage diverse health needs(123). These show that Government leadership is a key enabler of sustainable and context-specific AI integration in health systems.

5.5.2. Regulatory and Legal Issues

Ethical concerns, such as data privacy, security, transparency, accountability, trust, and bias, remain major barriers to the adoption of AI in healthcare in SSA(32). These challenges are compounded by the absence of robust legal frameworks to guide ethical and accountable AI deployment aligned with regional values(105). The policy landscape for AI in health is still nascent in most SSA countries, with few comprehensive national strategies or clear guidelines to govern ethical, equitable, and sustainable AI adoption(124). While some national strategies, such as Uganda's 4IR Policy and Nigeria's Data Protection Act, acknowledge AI's potential, they fall short of addressing core governance issues like algorithmic liability, AI-specific consent, or human rights-based oversight(108,125). Effective AI governance in Africa must be inclusive, context-sensitive, and rooted in local realities, highlighting the importance of addressing gender, equity, and indigenous knowledge(124). This calls for adaptive regulatory frameworks, alignment with existing continental initiatives, and stronger African participation in global AI policy discourse to promote ethical and responsible AI use in health(124).

Moreover, Africa lacks a continental regulatory or governance framework that ensures the ethical, responsible, and equitable use of AI(126). More broadly, most SSA countries still lack dedicated AI-for-health policies despite having general health and data regulations in place(124). Although more than 35 African countries had enacted personal data protection laws by mid-2023, their enforcement remains weak due to low public awareness of data rights and unclear responsibilities for data handlers(127). This underscores the urgent need for cross-sectoral legal frameworks and capacity building to ensure ethical and standardized health data use in SSA(127). Notably, the African Union's Convention on Cybersecurity and Personal Data Protection lacks provisions for individual compensation in the event of data breaches, unlike the EU's GDPR(128).

Here, Rwanda's AI chatbot pilot is a best practice example, successfully integrating the World Economic Forum's Chatbots RESET framework into routine healthcare processes(129). This framework promotes responsible AI use in healthcare, especially when clinical risks are involved(129). Here, the collaboration between developers and implementing health organizations enabled continuous feedback, risk management, and alignment with international standards(129).

5.5.3. Professional Bodies (Medical Associations, Professional Communities, etc.)

The South African Medical Association highlighted the crucial role of professional bodies in leading ethical and practical strategies for AI adoption, emphasizing medical leadership, clinician involvement, and inclusive governance to build trustworthy, accessible AI systems in primary care(130). Similarly, at its February 2025 seminar, the Health Community of West Africa Association emphasized the role of professional bodies in establishing regional AI governance, calling for ethical frameworks, standardization of AI diagnosis and treatment tools, and clinician-led regulatory oversight to ensure responsible deployment across West African health systems(131). Together, these examples demonstrate how professional bodies across SSA are pivotal in shaping ethical governance, fostering clinician engagement, and steering the responsible adoption of AI in PHC(130,131).

5.5.4. Socio-cultural Context

The Science for Africa Foundation's study reveals that most African countries have yet to meaningfully integrate gender considerations into their AI policies, with women, youth, and people with disabilities often overlooked in both policy design and implementation(132). Even when gender is acknowledged, practical enforcement remains weak due to fragmented coordination, limited resources, and low stakeholder awareness (132). Stark disparities in gender equity ratings across the continent further highlight the need for intentional, systemic action to close inclusion gaps(132). Intersectionality is essential for understanding and addressing the risks associated with AI in SSA. Biases in data and algorithms, the persistent digital gender divide, and the exclusion of marginalised voices, including women, LGBTQ+ individuals, and people with disabilities, can lead to harmful, unequal outcomes in AI-enabled health interventions(133). Without applying an intersectional lens, efforts to scale AI risk deepening existing inequalities(132). Limited access to digital tools and the internet among African women and girls, for example, creates a structural disadvantage in benefiting from AI technologies, especially when datasets and algorithms reflect dominant groups while excluding diverse lived realities(132). Building inclusive AI systems demands that governments, civil society, and tech developers centre diverse lived experiences in both design and policy from the outset(133). Moreover, the impact of colonial legacies remains a significant barrier to inclusive AI adoption in SSA. Experts from several African countries have emphasized how historical power structures continue to manifest in language disparities that limit access to education and AI-driven solutions(134). For instance, Luger et al. note that only 20% of the population in Mali is fluent in French, creating significant barriers to information access during the COVID-19 pandemic when public health tools were developed primarily in colonial languages(104). These examples reflect how colonial histories intersect with sociocultural and linguistic exclusion, further emphasizing the need for intersectional approaches in AI for health across SSA.

5.5.5. Inter-Organisational Networking

A promising solution here is Federated Learning, which allows institutions or health facilities to collaborate on model training by sharing their data, while maintaining privacy and patient data confidentiality(135). It was applied across 8 SSA countries and enabled effective AI model training without compromising patient data privacy, and showed improved generalization and accuracy of TB x-ray diagnosis(135). Similarly, another study demonstrated that federated learning can be effectively deployed on low-resource devices across diverse African settings, improving model generalizability in antenatal/fetal ultrasound(136). This highlights its feasibility and potential for scalable, real-world implementation while maintaining privacy(136).

Moreover, public-private partnerships (PPPs) are increasingly recognised as vital for scaling digital health solutions, including AI, across SSA(121). Governments are encouraged to engage private sector actors and regional blocs to secure sustainable financing and negotiate equitable terms(121). Recent evidence further highlights the role of such collaborations in strengthening AI governance and ensuring long-term integration into health systems(124). For instance, Zipline's AI-powered drone network in Rwanda and Ghana integrates with national health systems to optimize medical supply delivery to remote facilities, reducing delays, improving efficiency, and contributing to over 50% fewer postpartum hemorrhage deaths in Rwanda(137,138). Similarly, PATH, in partnership with local and international organizations in Kenya, is trialing an AI-powered CDSS in PHC, expected to produce real-world evidence by the end of 2025(139).

PPPs, such as AI labs in Ghana, Uganda, and South Africa, and startups like Intron Health and iCog Labs, demonstrate how inclusive, cross-sector collaboration among data holders, funders, and tech experts is critical to developing sustainable, context-specific AI in Africa(140). In Ethiopia, a collaboration between the Ministry of Health, Last Mile Health, and IDinsight led to HEP Assist, an AI tool supporting over 40,000 CHWs with real-time clinical guidance, showcasing how national alignment and technical expertise can accelerate AI adoption in rural primary care(123). The WHO emphasizes the need for ongoing collaboration between regulators, developers, and manufacturers to ensure the safe, effective, and ethical deployment of AI technologies(141).

5.5.6. Infrastructure

One of the most significant barriers to deploying AI applications in PHC SSA is the region's limited infrastructure, specifically, poor internet connectivity, unreliable electricity, and a shortage of digital devices(46,72). Fewer than one-third of health facilities in SSA have access to reliable electricity(105), and only about a third of the population can access internet services(44). This poses a major challenge, as many AI technologies rely on internet availability for cloud-based storage and computing(66). For instance, in Tanzania, a study exploring AI-based optimization of EHR systems in PHC identified low-bandwidth internet and frequent power outages as key constraints, leading to data loss and delays in patient care(73). Similarly, in Cameroon, healthcare workers raised concerns that limited internet access and a lack of smartphones could restrict the usability of an AI-based cervical cancer screening tool in their clinical settings(93).

Therefore, investing in digital infrastructure, such as solar power and satellite internet, is critical for AI integration in SSA, particularly to support last-mile health facilities (142). Solar energy provides a reliable, sustainable power solution for health facilities in off-grid and underserved areas. By integrating solar systems with battery storage, healthcare facilities can ensure the continuous operation of AI-driven diagnostics and data management, even in remote settings(143). Complementing this, satellite internet can provide high-speed, low-latency internet to remote facilities, enabling AI adoption in underserved areas where land connectivity is unreliable or absent, though regulatory frameworks must adapt to scale these solutions(144).

Table 1: Emerging best practices (promising solutions) in the adoption of AI in PHC in SSA

Emerging Best Practices	Description	Country / Region	References
Co-creation with end users	Co-creation fosters trust, usability, and user engagement, e.g., Hemophilia Chatbot Senegal	Senegal	(70)
Offline AI tools	Tools designed to function without constant internet, e.g., Ebola CDSS operable in offline mode. A key solution for rural and low-resource settings with limited internet.	Gambia, Malawi, Senegal, Sierra Leone	(68–71)
Interpretable or Explainable AI (XAI) solutions	Designed to be transparent and explainable, ensuring that stakeholders (e.g., clinicians, patients) can understand how the AI works and how decisions are made. This enhances transparency, trust, and ethical compliance.	Tanzania, Kenya	(42,76,79,80)
Language-inclusive AI	AI applications that incorporate African local languages and dialects, enabling better communication and trust.	Kenya, Rwanda, South Africa, Mali	(78,102–104)
Training and Upskilling Programs	Integration of AI training into CPD, medical/nursing curriculum, and on-the-job training to boost AI literacy and digital competence	*Several studies have underlined this	(100,115–119)
Federated Learning	A privacy-preserving AI training method that enables multiple institutions/facilities to train models collaboratively. It overcomes data privacy barriers and addresses data shortage in fragmented systems by enabling joint training.	Ethiopia, Ghana, The Gambia, Mozambique, Nigeria, the DRC, Senegal, and Uganda	(135,136)
AI-powered drone logistics delivery	AI-enabled drones integrated into national health systems for the rapid delivery of medical supplies (vaccine, blood, etc.) to remote or rural health facilities; reduced stock wastages, and decreased maternal mortality in Rwanda.	Ghana, Rwanda	(137,138)
Fostering Public-Private Partnerships	Collaborations between governments, NGOs, and the private sector to fund, develop, and scale AI. Zipline (Rwanda, Ghana), PATH in Kenya, and AI labs in South Africa, Uganda, and Ghana.	Rwanda, Kenya, Ghana, Ethiopia, South Africa, Uganda	(123,124,137–140)
Government-led AI initiatives	National AI policies and health sector leadership fostering innovation and regulation. Rwanda's AI strategy, Ethiopia's HEP Assist (led by the Ministry of Health), and country AI task forces across SSA.	Rwanda, South Africa, Kenya, Ethiopia	(117,120–123)
Ethical frameworks and regulatory alignment	Use of structured frameworks like RESET and aligning with global norms. Rwanda's chatbot pilot applied the Chatbots RESET Framework, integrated into public health operations.	Rwanda	(129)

Table 2: Summary of Influencing Factors for the adoption of AI in PHC in SSA

NASSS Domains	Influencing Factors		Reference
Technology	Barriers	Lack of or limited high-quality, well-structured representative data	(54–56)
		Bias from non-representative datasets	(44,62,63)
		Limited digital skills	(72–74)
		Limited internet bandwidth	(66,67)
		High infrastructure, development, and maintenance costs of AI tools	(81–83)
	Enablers	developing annotated local datasets	(64,65)
		offline functionality (working without internet)	(68–71)
		Interpretability/explainability of the model	(76,80)
		Demonstrated performance of AI models	(76–78)
Value Proposition	Barriers	Limited utility or low performance of an AI model	(59,85)
		Cost of implementation vs limited budget in PHC	(81–83)
	Enablers	Clear clinical utility or demonstrated value/benefit	(38,86)
		Long-term cost-saving or efficiency gains	(89–92)
Adopters	Barriers	Concerns over privacy, accuracy, and HCWs' dependence on AI	(93,94,96)
		Fear of job loss among HCWs	(95)
		Low level of literacy on AI	(73,75,96)
		Lack of training on AI	(74,96)
	Enablers	Transparency and Accountability in AI Systems	(97)
		Co-creation with end-users	(70)
		Training and capacity building programmes	(99,100)
		Language inclusion (user-centeredness)	(78,102–104)
Organisation	Barriers	Poor data infrastructure and limited interoperability	(32,105,107)
		Limited infrastructure (internet, facility, electricity) and funding	(32,41,44,99,108)
		Limited workforce capacity (digital skills, AI literacy, technical proficiency, etc.)	(109–111)
		Gaps in leadership skills and support	(110,116)
		Poor data governance and internal policy	(44,72,100)
		Poor workflow integration	(114)
	Enablers	Interoperability of data	(106)
		Thorough needs assessment and involvement of stakeholders throughout the process	(66)
		Investment in the local ecosystem	(41)
		Strong leadership and management	(115,118)
		Smooth integration with existing workflow	(113)
		Strong data governance and patient safeguards	(97)

Wider System	Barriers	Lacks dedicated AI-for-health policies	(124)
		Weak data protection enforcement and the absence of clear legal frameworks	(105,127)
		Lack of gender considerations in AI policies	(132)
		persistent digital gender gap	(133)
		poor internet connectivity, unreliable electricity, and a shortage of digital devices	(46,73,105,111)
	Enablers	Strong government leadership	(117,120–123)
		Adaptive regulatory frameworks	(124)
		Professional bodies/councils' involvement	(130,131)
		Public-Private Partnerships	(123,137–141)
		Investing in sustainable infrastructure	(142–144)

Chapter 6. Discussion

This review set out to examine the adoption of AI in PHC in SSA, focusing on barriers, enablers, and lessons learned across technological, adopter, organisational, and systemic levels, using the NASSS framework. The evidence points to the transformative potential of AI to strengthen PHC delivery through improving diagnosis, screening, health education, and resource allocation, among others. However, its integration remains constrained by entrenched infrastructural, socio-technical, ethical, and governance challenges. The findings call for a critical, systems-level approach to address these interlinked issues and promote responsible, equitable, and context-sensitive AI adoption.

The findings highlight a clear tension between the technical demands of AI tools and the realities of low-resource PHC settings in SSA. Many AI models require large, high-quality, and well-structured datasets, conditions largely unavailable in these contexts. This gap not only compromises model accuracy but also introduces risks of algorithmic bias when tools trained on external data are deployed locally. Offline functionality emerges as a critical enabler, addressing internet limitations while making AI tools more accessible to frontline workers; however, it might not work for large models. More importantly, cases of locally developed datasets and tools demonstrate that contextual adaptation significantly enhances both usability and performance. These observations reinforce the importance of aligning AI development with ground realities, rather than retrofitting global solutions. They also suggest that material design choices, such as training data, language, and connectivity requirements, can determine whether an AI tool is empowering or exclusionary. Responsible AI integration must begin with these material foundations in mind.

Moreover, stakeholder perceptions, especially those of health workers and patients, play a pivotal role in the success of AI implementation. AI adoption in PHC must be understood as a human interaction process, as HCWs are not merely users but active agents whose trust, clinical judgment, and emotional labour shape care delivery. The introduction of AI tools into the consultation room risks reshaping the patient–provider relationship in ways that are not fully understood. Concerns around job displacement, loss of clinical autonomy, data privacy, and data misuse have been documented. These illustrate that beyond technical efficacy, the acceptability and sustainability of AI depend on human-centered safeguards: embedded consent protocols, transparency mechanisms, and ethical oversight. Moreover, patients may be sceptical about engaging with AI-based tools, especially when interactions are perceived as impersonal or when digital literacy is low. These concerns signal a broader need for inclusive, user-centred design and aligned awareness programmes to foster trust, uptake, and responsible usage.

The capacity of healthcare workers to adopt and effectively use AI tools is also a critical determinant of successful implementation. While many frontline providers in SSA exhibit openness to digital innovations, widespread gaps in digital literacy and AI-specific training limit their ability to understand, trust, and operate AI systems. Without targeted upskilling and ongoing support, AI systems risk being underused or misunderstood and could perpetuate existing inequities. Therefore, providing tailored training on AI, integrating AI education into health training, and engaging HCWs in design, deployment, and evaluation, supported by continuous professional development for HCWs, is paramount. Engagement of end-users (HCWs, patients, community) generally fosters greater acceptability and relevance. Moreover, the impact of AI on patient-provider relationships and clinical workflows requires close examination. Health workers often express cautious optimism, recognizing AI's potential to support clinical decision-making and reduce workload burdens. However, concerns persist about the de-skilling of clinicians through over-reliance on AI recommendations.

Among all the factors, inadequate infrastructure is one of the most immediate and foundational in the adoption of AI in healthcare in SSA. Many PHC facilities, especially in rural areas, face persistent deficits in electricity, internet connectivity, and access to digital devices, rendering cloud-based AI tools impractical and limiting even basic digital innovation. These are not just technical barriers but reflect deeper systemic inequities that constrain the operational viability of AI, regardless of its technical sophistication. The promise of AI could remain theoretical without foundational infrastructure to support its deployment and use. In SSA infrastructural deficit is also compounded by chronic underfunding. While external donor funding from international organisations and philanthropic entities has catalyzed innovation, it often results in fragmented, short-lived pilots that fall short of sustainable integration. To transition from isolated experiments to fully embedded AI ecosystems, strategic, government-led investments are urgently needed, alongside coordinated donor support aligned with national health priorities. As highlighted in the CEIMIA report, such investments should prioritize local innovation hubs, data infrastructure, and capacity building to create the enabling environment required for AI to contribute meaningfully to PHC transformation across SSA.

Economic considerations are also crucial in assessing AI adoption in SSA PHC. While AI promises efficiency gains and improved health outcomes, its cost-effectiveness and opportunity costs remain underexplored. Initial investments in infrastructure, training, and AI development are high, and the long-term sustainability of AI tools also requires ongoing financial and technical support, resources that are often limited in SSA health systems. The prevalent model of externally funded, NGO-led pilot projects often results in fragmented initiatives with limited scalability and sustainability, as discussed earlier. Without deliberate strategies to transition these pilots into government-led programs, there is a risk of perpetuating dependency on external actors and private sector monopolies. Such dependency may threaten equitable access and national digital sovereignty. Therefore, developing viable business models for AI in PHC, balancing public sector leadership, private sector innovation, and donor support, is crucial. PPPs have emerged as promising mechanisms to mobilize resources, expertise, and infrastructure. Rwanda and Kenya have demonstrated how national AI strategies combined with PPPs can drive contextually relevant innovation. Drone delivery networks powered by AI in Rwanda and Ghana also exemplify successful cross-sector collaboration that improves health outcomes while fostering sustainability.

Furthermore, ethical and regulatory challenges represent a critical axis shaping AI adoption in SSA. Despite over 35 African countries enacting data protection laws, enforcement remains inconsistent, and few have developed AI-specific ethical frameworks tailored to the local context. The absence of clear legal guidelines around liability in the event of AI errors exacerbates stakeholder concerns. Questions about who is responsible for harm caused by AI, whether developers, health workers, or institutions, remain largely unresolved. Fragmented governance structures and overlapping institutional mandates, as observed in countries like Nigeria, create regulatory confusion and weaken public trust. Additionally, digital sovereignty and the geopolitical context add layers of complexity. Much of the AI technology and datasets originate from high-income countries, raising concerns about digital colonialism, the risk that SSA health systems may become dependent on foreign technologies and data, potentially compromising autonomy and local agency. Moreover, the lack of a harmonized, pan-African AI governance framework highlights the urgent need for context-sensitive, inclusive, and rights-based policies developed with broad stakeholder participation.

Taken together, these findings highlight that AI in PHC cannot be reduced to technical interventions alone; it is an inherently socio-technical venture, shaped by interlinked infrastructural, socioeconomic, cultural, ethical, and geopolitical factors. Weak infrastructure hinders not just tool deployment but also data collection and feedback loops needed to improve algorithms. Poor training limits meaningful use and may undermine patient safety. Ethical and legal ambiguities corrode trust, while economic and geopolitical imbalances reinforce dependency. Importantly, these issues are not isolated; they amplify one another. For example, limited infrastructure leads to poor data quality, which in turn worsens algorithmic bias, reducing tool accuracy and eroding user trust. Addressing one issue without the others is unlikely to yield a sustainable impact.

Despite these challenges, emerging best practices are beginning to take shape. Successful AI adoption in PHC across SSA often shares key features: strong government leadership, alignment with national health goals, and strategic partnerships across public and private sectors. Countries like Rwanda have demonstrated that coordinated policies, investments in health tech ecosystems, and regulatory clarity can enable responsible innovation. On the technical front, designing AI for real-world constraints has proven essential. Offline-capable tools, low-power devices, and mobile-first platforms have greater potential for scale. Innovations in local African languages, driven by open-source communities, are helping to bridge linguistic divides and reduce exclusion. Efforts to decentralize model training while safeguarding patient data (Federated Learning) signal an important shift toward more context-sensitive, privacy-preserving innovation. It also opens the door for regional collaboration in building robust, generalizable models without centralized data sharing. Moreover, AI tools that are interpretable, explainable, and transparent are more likely to be trusted and sustained. Finally, user-centred and inclusive design is a foundational principle. Projects that involve health workers and communities from the outset, through co-creation, piloting, and feedback, are more likely to have higher adoption, greater satisfaction, and better outcomes. And embedding feedback loops, continuous evaluation, and adaptive learning processes is key not only to safety but also to long-term effectiveness.

The NASSS framework proved highly relevant in structuring the analysis, offering a flexible yet systematic lens to explore the socio-technical dimensions of AI adoption in PHC in SSA. However, it lacked explicit attention to infrastructure, power dynamics, and equity, issues central to this context. These were accommodated through thematic extensions such as a sub-section on infrastructure, inductive synthesis in the Adopters domain, and a critical lens on equity. While effective overall, future studies would benefit from adapting the framework to better capture these contextual nuances, particularly around infrastructure, inclusion, and systemic inequities shaping AI implementation in low-resource settings.

Chapter 7: Strengths and Limitations

This study has some limitations. The field of AI in PHC is still nascent in the region, and evidence on long-term sustainability or post-adoption impacts remains limited. Many of the included studies were country-specific pilots, limiting regional generalisability across SSA's diverse health systems. Most available literature focuses on early implementation, with few evaluations of mature systems. Moreover, the rapid pace of technological advancement means that new tools and research are constantly emerging, potentially bringing new findings soon. As such, this review provides a snapshot of a fast-evolving space and should be interpreted with this temporal context in mind. However, the study has several strengths and insights. A key strength of this study is its systems-oriented, context-aware analysis of AI adoption in PHC across SSA. It goes beyond technological optimism to explore real-world barriers, enablers, and scalable solutions. Using the NASSS framework allowed for a structured yet flexible lens to capture the complexity of AI integration. The study also brings together diverse insights from both peer-reviewed and grey literature sources. It centers region-specific examples and highlights local innovations and voices. This grounded, policy-relevant approach offers a detailed understanding of what is needed to responsibly and sustainably scale AI within primary healthcare systems in SSA.

Chapter 8. Conclusion

This review highlights that while AI holds significant promise to transform PHC in SSA, its successful integration depends on addressing interlinked technical, adopter, infrastructural, and governance factors. AI tools such as CDSS platforms, triage applications, and diagnostic support demonstrate early potential in improving care delivery. However, these innovations remain largely limited to pilot phases, constrained by limited data, infrastructure gaps, fragmented governance, and insufficient provider training.

Key barriers such as the use of non-local datasets, limited digital infrastructure, and low digital literacy must be addressed in tandem. Tools trained on data from high-income countries often perform poorly in African settings, risking bias. Without reliable internet, electricity, or interoperable systems, even well-designed AI tools risk becoming obsolete. Furthermore, digital illiteracy and skepticism among healthcare workers and patients can hinder adoption, and need to be addressed through training and support.

The review also shows that enabling factors, such as inclusive co-design, offline compatibility, language inclusion, PPPs, and policy alignment, can support AI integration at scale. Evidence demonstrates that government-led, context-aware, user-driven innovation can bridge infrastructure and trust gaps, provided there is sustained investment and multisectoral coordination.

Ultimately, AI adoption in PHC in SSA will not succeed through technology alone. It requires a systems-level, equity-driven approach that places frontline health workers, patients, and local realities at the center of innovation. Strategic investment, strong governance, and inclusive engagement must converge to unlock the transformative potential of AI in building stronger, more resilient primary health care systems across the region.

Chapter 9. Recommendation

The following recommendations reflect high-priority actions grounded in SSA's current capacity, technological readiness, and political will. They aim to enhance feasibility, promote ethical and effective adoption of AI, and enable scale-up of innovations that can genuinely strengthen the PHC system across the region. Of course, continued research is crucial to generate more local evidence and a clearer understanding of the factors and solutions.

A. For Ministries of Health

1. Prioritise Investment in Digital Health Infrastructure

To make AI adoption viable, Ministries of Health must invest in foundational infrastructure, such as reliable internet connectivity, digital health records, and power supply, in PHC settings. While large-scale funding may be constrained, public-private partnerships and donor coordination can offer feasible financing models. Prioritising scalable and open-source digital platforms also reduces costs and fosters long-term sustainability.

2. Strengthen Capacity through Targeted Workforce Training

Ministries should design and roll out capacity-building initiatives that train frontline PHC workers, health policymakers, and leaders/managers on the ethical use, interpretation, and limitations of AI tools. Training must be tailored to local languages, literacy levels, and clinical contexts, and should be incorporated into national continuous professional development programmes. Partnering with local academic institutions can improve reach and reduce dependency on external consultants.

3. Develop and Implement National AI Piloting Guidelines

To move beyond fragmented pilot projects, ministries should create national guidelines for piloting and scaling AI innovations. These should include requirements for local stakeholder involvement, alignment with health system priorities, and documentation of lessons learned. A central repository for pilots can help track progress, reduce duplication, and guide evidence-based scale-up decisions. More research and evidence can provide learning and guide future improvements.

4. Develop National Policies and Regulatory Frameworks for AI in Health

National MoH should develop clear, context-specific policies to regulate the ethical and effective use of AI in healthcare. These frameworks should address data privacy, algorithm transparency, patient safety, and liability, while aligning with existing digital health strategies and data protection laws. MoH can leverage intersectoral coordination platforms and stakeholder consultations to draft feasible policies. Support from regional bodies and development partners can provide technical assistance and policy templates to enhance the effectiveness of these initiatives. And phased implementation ensures alignment with national capacity and resource constraints. Further local research and evidence can guide more contextualization of AI for Health policies.

B. For AI Developers

1. Co-Create Locally Adapted AI Solutions

Developers must work closely with local health workers, patients, and policymakers from the outset to co-design AI tools that are relevant, usable, and culturally appropriate. This involves building tools using locally representative data, where possible, and ensuring that interfaces are intuitive for users with limited digital literacy. Here, creating lightweight, offline-compatible, and language-inclusive models increases applicability in rural or low-resource settings. Moreover, collaborations with local research institutions and ministries can facilitate access to relevant data and field-testing environments.

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Annex 1: Key words for Search Strings (Adapted for PubMed, Scopus, and Google Scholar)

Technology	AND	Healthcare Context	AND	Geographic Context	AND	Adoption Factors
Artificial Intelligence, or		Primary Healthcare, or		Sub-Saharan Africa, or		Adoption, or
Machine Learning, or		Primary care, or		Africa, or		Implementation, or
Deep Learning, or		Rural Health, or		Developing Countries, or		Integration, or
Neural Network, or		Community Health, or		LMICs, or		Barrier, or
Large Language Models, or		Health System, or		Angola, or		Enabler, or
Natural Language Processing, or		Healthcare, or		Benin, or		Challenges, or
Clinica Decision Support System, or		Healthcare System, or		Botswana, or		Facilitators, or
Chatbot, or		Healthcare Worker, or		..... all SSA countries until		Efficiency, or
		Clinic(s), or		Tanzania, or		Cost-effectiveness, or
		Practitioner, or		Togo, or		Sustainability, or
		Patients.		Uganda, or		Scale-up, or
				Zambia, or		Spread
				Zimbabwe.		Readiness
						Adaptation
						Lessons Learned, or
						Best Practices, or
						Policy, or
						Governance, or
						Regulation,

Annex 2: Declaration of AI Use

Check the box that applies to your completion of this assignment:

☐ I confirm that **<u>I have not used</u>** any generative AI tools to complete this assignment.

☒ I confirm that **<u>I have used</u>** generative AI tool(s) per the "**Guidelines for the use of Generative AI for KIT Institute Master's and Short course participants".** Below, I have listed the GenAI tools used and for what specific purpose:

Generative AI tool used	Purpose of use
1. Perplexity	To brainstorm on the initial thesis topic choice and refine my research question,
2. Chat GPT	For conceptual clarification, brainstorming for the structure and outline of my chapters, and getting a perspective on unfamiliar topics.
3. Grammarly	For grammar, spelling, and punctuation checks.