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Is the public sector Africa's hidden force for AI-driven healthcare transformation?

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ABSTRACT

The transformative impact of Artificial Intelligence (AI) in today's interconnected world is extensive, reshaping capabilities, enhancing efficiencies, and creating pathways to address critical global challenges. AI demonstrates potential in healthcare for improving outcomes through enhanced diagnostics, predictive analytics, and personalized treatment plans, directly contributing to Sustainable Development Goal 3 (SDG 3) on good health and well-being. However, the benefits of AI remain unevenly distributed, with notable gaps in adoption and access, particularly in lower-resource regions like Africa. This paper conducts a comprehensive scoping review to examine the role of the public sector in advancing AI integration within African healthcare systems. The key contributions include: (1) synthesizing existing research to identify trends, gaps, and progress in AI adoption, (2) highlighting practical examples of AI applications that show promise in improving healthcare delivery, (3) analyzing the major barriers to widespread adoption, and (4) outlining policy implications and actionable recommendations. The discussion is framed around six core components of a sustainable AI ecosystem: skills development, data access, computational resources, supportive policy environments, financing, and multi-sector partnerships. The findings suggest that with coordinated public sector leadership, strategic investment, and effective policy implementation, AI can improve healthcare outcomes and support sustainable development across the continent.

1. Introduction

A healthy population is essential for a country's economy, as the well-being and productivity of its citizens directly influence the nation's overall economic prosperity and stability [1,2]. As a result, governments across the globe have regarded investments in healthcare enhancement as a strategic approach toward fostering economic growth and ensuring sustainable development. This aligns with Goal 3 of the 2030 Agenda for Sustainable Development adopted by the United Nations General Assembly in 2015 [3]. As the world strives to accelerate progress towards the Sustainable Development Goals (SDGs), the transformative impact of digital technologies, including Artificial Intelligence (AI), is mentioned as an important tool to aid such initiatives [4]. Recent advancements in AI technology present unprecedented opportunities for the application of AI across different angles in the healthcare domain – including epidemic surveillance [5–7], disease prediction, and precision medicine [8,9]. However, the progress in AI adoption in healthcare has been significantly uneven, primarily concentrated in the Global North. Meanwhile, countries in the Global South, especially Africa, lag in AI adoption in the healthcare sector. As depicted in Fig. 1, the Government AI Readiness Index 2024 Report [10] underscores this disparity, placing Sub-Saharan African (SSA) countries at the lower end of Government AI Readiness rankings. According to the report, in 2024, SSA countries recorded an average score of 32.7, in contrast to 82.6 reported for North America, highlighting a noticeable global disparity. Moreover, the AI Index 2025 Annual Report by Stanford University underscores disparities in global AI adoption. Notably, while the global count of AI-related publications more than doubled between 2013 and 2023, SSA countries accounted for only 0.89 % of the total output during this period, highlighting the region's limited contribution to global AI research. The study on the global spread of AI in the public sector further supports this [11]. Such disparity is contributed to by limited infrastructure, insufficient funding, and a limited number of skilled AI professionals, collectively hindering the continent's ability to leverage AI advancements. Consequently, while AI is driving improvements in healthcare globally, African healthcare systems still face challenges such as inadequate health service planning, shortage of human resources, and poor utilization of quality data for decision-making [12]. To bridge this gap,

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strategic investments and policy frameworks are essential for fostering AI adoption in African healthcare, enabling the continent to catch up with global advancements and fully benefit from AI's capabilities to revolutionize healthcare.

The analysis in this paper is organized around six essential components of an AI ecosystem: skills development, data access, computational resources, supportive policies, funding mechanisms, and strategic partnerships. Such components form an interdependent ecosystem that must function cohesively. Skilled professionals are essential to develop, deploy, and maintain AI systems, but their effectiveness depends on the availability of high-quality, representative data and adequate computational infrastructure to process it. Funding enables both the acquisition of infrastructure and the development of capacity-building initiatives to address skills gaps. At the same time, policies and regulatory frameworks guide ethical use, data governance, and standards, ensuring responsible and inclusive deployment. On the other hand, strategic partnerships—across government, academia, the private sector, and civil society—facilitate knowledge exchange, innovation, and resource sharing. These elements interact dynamically: for example, investments in computing infrastructure can attract partnerships; progressive policies can unlock funding; and data availability can drive innovation and consequently skills development.

This paper is based on the premise that public sector involvement is fundamental to large-scale AI adoption in Africa's healthcare. In Tanzania, for instance, it is estimated that in 2023, 59 % of health facilities were run by the government, and the rest were either private or faith-based [13]. Besides, most primary healthcare facilities are operated by the government and serve as the important entry point into the healthcare system for the majority (95 %) of the population [14]. Moreover, the 2023 East Africa healthcare market insights report suggests that, generally, the public sector continues to dominate the healthcare industry, although private healthcare providers are increasingly entering the market. According to the report, in Rwanda and Ethiopia, most of the facilities are owned and operated by the government, whereas 50 % and 45.8 % are owned by the public sector in Uganda and Kenya, respectively [15]. A similar trend has also been reported in South Africa [16] and other African countries. This provides evidence that realizing the large-scale application of AI in healthcare requires the involvement of the public sector. Notably, given the number of public-operated health facilities, the public sector can contribute to the availability of quality clinical data, which is fundamental for training and validating AI models. Moreover, the sensitivity of the healthcare domain and the increasing concerns about AI's ethical issues, including transparency, biases, and privacy, further accelerate the need to regulate the implementation of AI solutions. One of the key players in regulating AI is the public sector [17], which is mandated to draft policies, strategies, and regulations across different sectors. Besides, the public sector (e.g., Ministry of Health or equivalent government bodies) oversees and regulates healthcare in the country. Consequently, while the private sector contributes to AI innovation, public sector involvement is important for establishing the necessary infrastructure, policies, and inclusive strategies to ensure equitable and widespread AI adoption. To this end, this paper utilizes a scoping review methodology to provide a comprehensive overview of how the public sector can accelerate AI adoption. By systematically mapping the existing literature, this study identifies key strategies, challenges, and opportunities that can inform policy and decision-making processes aimed at integrating AI technologies into public healthcare systems.

The remainder of this paper is organized as follows. Section 2 highlights AI adoption in healthcare and summarizes existing initiatives in Africa. Section 3 describes the materials and methods applied in this study. Section 4 presents the study results, followed by the discussion and recommendations in Section 5. Finally, Section 6 concludes the paper.

2. AI in healthcare

Artificial intelligence possesses transformative power, and its potential is profoundly impactful across various sectors, including healthcare. The integration of AI in healthcare has led to advancements in diagnostics, personalized medicine, and patient care management, underscoring its far-reaching capabilities [18,19]. Research suggests that AI tools can harness extensive datasets to detect patterns, often exceeding human performance in various healthcare domains. For example, the study by Kim et al. [20] showed that an AI algorithm trained on large-scale mammography data has demonstrated superior diagnostic accuracy in detecting breast cancer compared to radiologists. In another study, an AI system outperformed radiologists in breast cancer prediction and attained an absolute reduction of false positives and false negatives in interpreting mammograms [21]. Similar results have also been reported in detecting pneumonia [22] and Coronavirus Disease (COVID-19) [23] in chest radiographs, skin cancer [24,25], diabetic retinopathy [26,27] and cardiac rhythm disorders [28]. Besides disease prediction, AI systems have demonstrated high accuracy in recommending treatment plans. These systems utilize large datasets to analyze patient information and medical literature, providing evidence-based treatment suggestions that often rival or surpass human expertise. For instance, IBM's Watson for Oncology analyzes vast

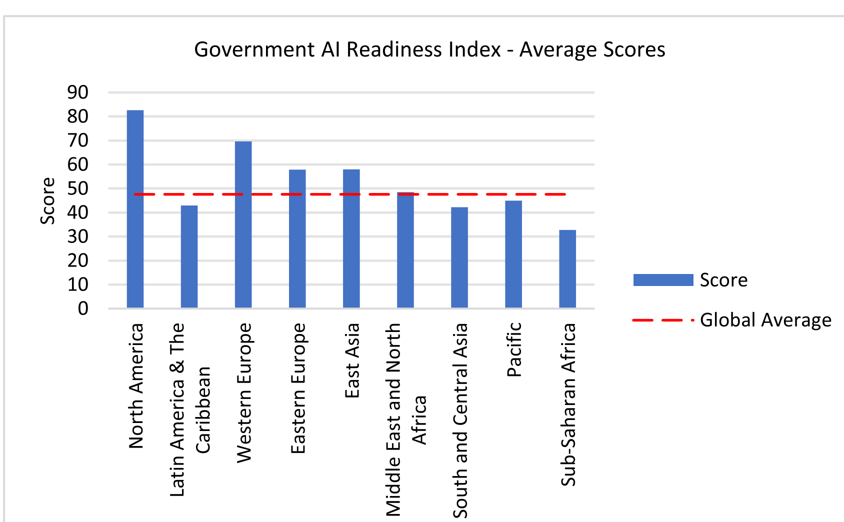

Fig. 1. Government AI readiness index regional average scores [10].

amounts of data from clinical test cases and medical literature to offer personalized cancer treatment recommendations, showing high concordance with expert oncologists' decisions [29]. Furthermore, studies have shown that AI-driven platforms can effectively recommend treatments for various conditions, improving patient outcomes and reducing the likelihood of errors [30,18]. Moreover, using AI to automate administrative tasks greatly improves the efficiency of hospital operations. This shift allows healthcare professionals to dedicate more time to patient care instead of administrative responsibilities, ultimately enhancing the quality of healthcare delivery [31,32].

In the context of Africa, where structural healthcare challenges—such as limited infrastructure, workforce shortages, and fragmented data systems—are prevalent, the integration of AI into healthcare dates back to early 1980s pilot projects in countries like South Africa, Kenya, Egypt and Gambia. Notable early examples include the Computerized Aid To Treat (CATT) system in South Africa, used in drug prescriptions by nurses. In 1986, a medical artificial intelligence tool developed in the US was piloted in Egypt to detect common blinding eye disorders [33]. In recent times, although the healthcare application of AI in Africa remains relatively low, several notable initiatives are emerging across the region. For instance, innovations like PapsAI, Hurone AI, DataPathology, SarataniAI and MinoHealth have been introduced to leverage AI for cancer diagnosis through cervical cell image analysis, tissue analysis, disease forecasting, and teleradiology [34]. Moreover, several other studies have been proposed and reported positive results in the diagnosis and prognosis of cervical cancer, leukaemia, colorectal cancer, and breast cancer [34]. In obstetric care, Adedinsewo et al. [35] reported positive results in a clinical trial to evaluate an AI-powered electrocardiogram for cardiomyopathy detection among pregnant and postpartum women in Nigeria. AI-powered computer vision technology was assessed in Kenya to determine its effectiveness in interpreting images of HIV self-testing results. The AI tool achieved competitive results compared to pharmacy providers and clients. The study concluded that AI can serve as a quality assurance tool for HIV (human immunodeficiency virus) testing, especially in identifying false-negative test interpretations that humans commit. The qXR software, which utilizes deep learning, was evaluated in South Africa to assess its effectiveness in detecting lung cancer and Pulmonary Tuberculosis (PTB). The results indicate that the tool demonstrates high sensitivity and specificity in analyzing chest radiographs, suggesting its potential to assist in the early detection of these diseases [36]. These tools are vital for resource-constrained healthcare systems, especially in regions with a high burden of PTB and lung cancer. Initiatives such as Zindi Africa have also created spaces for data science communities to build machine learning solutions tailored to local healthcare problems, while AI was used for disease modelling and contact tracing during the COVID-19 pandemic.

Despite these advancements, AI in African healthcare faces several setbacks. A primary barrier is the scarcity of high-quality, digitized, and interoperable health data, which limits the development of contextually relevant AI solutions and contributes to biased models trained predominantly on data from the Global North [33,37]. Additionally, a noticeable skills gap persists [38,39], marked by a shortage of AI professionals, healthcare researchers, and interdisciplinary experts capable of driving innovation. Ethical and regulatory concerns—such as data privacy, algorithmic transparency, and fairness—remain largely unaddressed, often due to the absence of national AI strategies [40]. Nevertheless, promising responses have emerged. The African Union's Digital Transformation Strategy (2020–2030) designates AI and other emerging technologies as key enablers of sustainable development, while regional initiatives such as the International Development Research Centre's (IDRC) AI4D Africa program and UNESCO's global AI ethics framework are actively promoting capacity-building, governance, and policy support across the continent.

3. Materials and methods

This study employs a scoping study methodology, as outlined by Arksey and O'Malley [41], to synthesize available literature on the role of the public sector in accelerating AI adoption in healthcare in Africa. The scoping study approach is essential in providing a detailed description of findings and the breadth of research, offering a way to summarize and share research outcomes with policymakers, practitioners, and the public [41]. The methodology follows a structured process involving the identification of the research question, selection of relevant studies, data charting, and the synthesis and reporting of results [42].

3.1. Research question

This study aims to answer the research question: What initiatives can the public sector take to promote AI adoption in healthcare across Africa? By examining the reported challenges and opportunities in adopting AI-driven healthcare solutions, this study aims to identify and document existing initiatives while highlighting necessary public sector interventions to accelerate AI adoption in African healthcare.

3.2. Finding data sources and search strategies

To identify candidate papers, we systematically searched, gathering studies from academic journals, conferences, and workshops. This involved sourcing relevant papers from five reputable digital libraries: PubMed, ScienceDirect, ACM, Springer, and Willey. Our search targeted publications from the past five years (2019 to 2023), focusing on AI adoption in African healthcare. We used primary keywords—Artificial Intelligence and Healthcare—and combined them using logical operators (ANDs and ORs) to form inclusive search terms. These terms were further enriched with additional keywords such as AI, Machine Learning, Africa, developing countries, public sector, and government to create search strings or queries. The authors conducted the initial search and verified it by three other reviewers to ensure accuracy and completeness. The collected studies were then thoroughly examined to ensure a comprehensive and systematic review of existing initiatives.

3.3. Selecting the candidate papers

A comprehensive search across five digital libraries returned a total of 303 studies related to the topic. Inspired by Kitchenham and Charters [43], and Brereton et al. [44], the study selection process was divided into preselection and final selection phases. During the preselection phase, specific search strings were used to identify relevant studies that were consequently reviewed based on titles, abstracts, keywords and conclusions. This initial screening eliminated duplicates and irrelevant studies, narrowing the pool to 138 papers. An additional 22 papers were identified using backward and forward snowballing techniques as described in [45], which involved examining references and citations of the initially selected papers to uncover more relevant studies. This rigorous selection process ensured the comprehensive inclusion of pertinent literature. In the final selection phase, a full-text review of the 160 papers was conducted, resulting in 27 studies that met all inclusion and exclusion criteria summarized in Table 1. The distribution of the

Table 1
Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
Peer-reviewed academic publications Papers published in English Papers published between 2019 and 2023 Studies primarily focused on AI and healthcare in the context of Africa	Papers that have not undergone peer review Papers that are not published in English

papers retrieved from each digital library is presented in Table 2.

3.4. Data charting

Each study in our final selection was systematically reviewed, and key data was extracted using a standardized charting form. This process involves capturing essential information such as the study's objectives, the specific initiatives identified, the role of the public sector, and any reported outcomes or impacts of these initiatives. The data was organized into categories and themes to reveal patterns and trends in the literature. This approach, as outlined by Arksey and O'Malley [41], and further refined by Levac et al. [46], ensures a comprehensive overview of the research landscape and aids in identifying insights relevant to advancing AI adoption in healthcare. This methodical data charting supports a robust synthesis of findings, facilitating the extraction of actionable recommendations for policymakers and stakeholders in the healthcare domain.

Thematic analysis was then applied to identify the contents required from the charted data. This involved coding the data for recurring themes, categorizing them, and interpreting their significance within the context of AI adoption in healthcare. Thematic analysis helps to uncover underlying patterns and relationships in the data, providing an understanding of the various public sector initiatives and their impacts. Methodologies outlined by Braun and Clarke [47] support this analytical approach, which emphasizes a systematic theme identification and analysis process, ensuring the findings are comprehensive and contextually relevant. This detailed thematic analysis enriched the scoping study by offering deeper insights and facilitated the formulation of targeted recommendations for enhancing AI adoption in African healthcare.

4. Results and discussion

In this section, we present the core findings of the review and discuss their implications for accelerating AI adoption in Africa's healthcare sector. Table 3 provides a summary of the key challenges identified in the literature, along with proposed solutions. The following subsections offer a detailed examination of these findings.

4.1. Clinical datasets

Machine Learning (ML) algorithms use clinical data to train computational models and generate predictive insights to guide clinical decision-making [59]. However, data accessibility poses a critical challenge in machine learning applications in the health sector [60]. Public hospitals can contribute to machine learning by aggregating and sharing diverse anonymized patient data, enhancing the quality and breadth of clinical data available for research and innovation. For example, in the US, the federal government and public stakeholders have allowed open access to clinical data to promote innovations in healthcare [61]. In Africa, however, Owoyemi et al. [33] suggest that the low level of digitization poses a challenge to the limited availability of locally generated clinical data essential for building AI systems. For example, Mwanga et al. [48] proposed a Logistic Regression model combined with Mid-infrared (MIR) spectroscopy for malaria screening using dried human blood spots. Yet, the deployment of this model in real-world scenarios was hindered by the lack of representative datasets required for thorough validation and ongoing improvements. Similarly, Manson et al. [37] suggest that the scarcity of AI systems in radiotherapy is primarily due to the limited availability of sufficient radiological images required for training deep learning algorithms. This issue is further compounded by the prevalence of imbalanced, biased and poor-quality data, which not only obstructs the deployment of machine-learning models [52,12,53] but also exacerbates problems like model overfitting, underfitting, and biased decision-making [49,34]. Several studies have reported the issue of data scarcity and incompleteness [12,50,51], demonstrating how it can result in deploying algorithms predominantly developed outside the continent [56]. Importantly, while clinical data is not always scarce, a portion of the data generated remains underutilized due to challenges in storage, management, and the inherent complexity of the data itself [54]. Currently, most health facilities in SSA rely on a patchwork of Health Information Systems (HISs), ranging from non-digitized records to limited, facility-specific electronic systems [62,63]. This could result in fragmented data, inconsistent quality, and poor interoperability. Several African countries have initiated improvements in their HISs to enhance

Table 2
Distribution of the papers reviewed.

SN	Digital Library	Retrieved Papers	Pre-selection stage	Final Selection
1	PubMed	58	43	12
2	ScienceDirect	75	31	6
3	ACM	92	37	5
4	Springer	47	11	2
5	Willey	31	16	2
Total		**303**	**138**	**27**

Table 3
Summary of the reported challenges in the reviewed literature.

Purpose of the study	Reported Challenges	Proposed Solutions	Reference
■ Predicting malaria ■ Diagnosing dermatological conditions	Insufficient and/or incomplete datasets	NA	[48–51]
■ Predicting cholera epidemics ■ Pediatric ultrasound interpretation	Poor data quality	A review of healthcare systems and tools to facilitate quality data collection	[52,53]
Risks prediction and diagnosis of Congenital Heart Defects	Poor data storage and management, and complex data	Implementation of big data technologies	[54]
Exploring the use of AI in healthcare	Limited access to large volumes of high-quality data, data privacy, lack of policy and limited resources necessary for AI deployment in healthcare	Strengthening the enabling environment for AI adoption in the healthcare sector	[12]
Cancer care	Patients' data privacy, security and confidentiality. Limited understanding of AI usefulness among patients	Patients should be informed about AI diagnostic tools and assured of their privacy protection	[34,55]
Radiotherapy	■ Insufficient data ■ Limited AI awareness ■ Lack of funding and AI resources	■ Creating national data banks ■ Developing AI training programs ■ Investing in AI infrastructure	[37]
Screening Diabetic Retinopathy	Suboptimal telecommunication network and limited computing power	Integrating AI directly into retinal cameras or deploying AI as a standalone system	[27]
Regulatory challenges for AI in healthcare	Lack of policy and legal frameworks that regulate and encourage AI innovations	Development of national AI policy and legal frameworks	[56–58, 34]

data availability, adopting a data warehousing approach supported by the District Health Information System (DHIS2) software. However, the absence of cohesive national health information management strategies undermines the performance of these systems [64]. The Africa Centres for Disease Control and Prevention (CDC) initiative to bolster health information systems across member states and implement a continental data-sharing platform represents a crucial step forward [65]. However, much work remains to ensure these efforts translate into tangible improvements in AI system development and deployment across the continent.

To optimize the accessibility of clinical data, the public sector must consider digitizing healthcare and establishing regulations and strategies to facilitate the management of integrated HISs [64,66]. In digitizing healthcare, emerging technologies like the Internet of Things (IoT) [67] can be leveraged. IoT devices generate vast amounts of real-time data that can fuel AI models, but also benefit from AI's ability to analyze and act on this data for smarter automation. That would consequently contribute to the advancement of AI in healthcare, ultimately leading to more efficient healthcare delivery and improved patient outcomes. The African Union (AU) Continental Artificial Intelligence Strategy 2024 [38] highlights that the public sector can contribute to AI development by generating digital datasets from government databases and making them publicly accessible through national open data portals. Several studies suggest that the extensive adoption of electronic medical records and accessible large-scale medical databases or national data banks will promote the development of AI solutions tailored to Africa [33,68,37]. Furthermore, enhancing data quality and interoperability through the standardization of data formats is essential for streamlining data integration across health systems. Investments in secure data infrastructure are also necessary to protect patient privacy and comply with safety and ethical standards. As highlighted by the World Health Organization (WHO) Global Strategy on Digital Health 2020–2025 [69], technologies like AI and tools for secure data storage and exchange across the health ecosystem have demonstrated potential to improve health outcomes. Public sector initiatives should also emphasize training healthcare professionals in data literacy and AI applications, enabling them to leverage AI tools effectively. For instance, a study involving 1020 radiographers across 28 African countries revealed that 92.5 % of the respondents expressed the need for training to accelerate AI adoption in medical imaging [70]. Notably, 57 % of the respondents were from public health facilities, and 6.3 % were from quasi-governmental health facilities. It is worth noting that a few African countries, for example, Nigeria, Senegal, Ghana, Sierra Leone, South Africa, and Rwanda, are beginning to acknowledge the significance of data and its role in advancing AI development. These countries have already developed data strategies emphasizing open government data, data literacy, data utilization, and data infrastructure [38].

4.2. AI infrastructure

As AI models grow in scale, they generally become more accurate and capable. However, this increase in model size also leads to higher computing requirements, which, in turn, results in greater energy demands [71]. In other words, the training and inference phases of AI models require extensive computing power and reliable electricity. However, Africa has a dearth of such facilities. As of 2022, 43 % of Africa's population still lacked access to electricity, with the majority residing in Sub-Saharan Africa. Frequent power outages in the region are known to disrupt Information and Communication Technology (ICT) systems and infrastructure [72], making it difficult to run AI systems that require a continuous power supply. Moreover, the computing infrastructure required for AI goes beyond standard hardware and involves specialized components such as Graphics Processing Unit (GPU) and Tensor Processing Unit (TPU), which are essential for handling resource-intensive AI workloads. Access to such high-performance computing infrastructure is often limited due to high costs and limited local manufacturing. Consequently, hindering the development, training, and deployment of AI models, creating a dependency on foreign cloud providers and external data centers, which in turn raises concerns about data sovereignty, latency, and long-term sustainability. Besides, the substantial storage capacity needed by AI systems translates to an increasing demand for data center space. As of August 2024, Data Center Map statistics reveal that Africa hosts only 1.7 % of the world's data centers, distributed across just 26 countries on the continent. Research indicates that as of 2023, machines located in the United States, Germany, and China account for 60 % of the systems featured on the TOP500 list of supercomputers [73].

On the other hand, cloud computing offers an alternative to on-premise AI infrastructure by providing scalable storage and computing power. This enables handling large datasets and complex computations without significant upfront investments in physical hardware. Despite the clear benefits of cloud computing services, privacy and security remain a challenge due to the remote processing and storage of sensitive data, such as patient medical records [74–76]. Besides, accessing cloud computing services requires reliable and quality internet connectivity with substantial bandwidth, which is often challenging in Africa [77]. According to the International Telecommunication Union (ITU) 2023 report, only 37 % of the population in Africa uses the Internet, and the most prevalent broadband technology is 3 G. In this context, increased research and investment in Edge AI are essential to address challenges posed by cloud computing. In contrast to cloud computing, Edge AI utilizes edge devices (e.g., smartphones and IoT devices) with substantial computing power to process data in real-time, offering localized intelligence and minimizing latency and bandwidth usage [78,79]. Moreover, to address privacy concerns associated with transferring data to the cloud, a privacy-preserving AI framework such as Federated Learning (FL) can be employed. FL enables devices to share only model parameters rather than raw data, thereby safeguarding sensitive information [80].

The lack of adequate infrastructure hampers the widespread adoption of AI across the continent. For instance, the usability of an AI tool developed by Bellemo et al. [27] for screening vision-threatening Diabetic Retinopathy (DR) in Zambia was limited by a suboptimal telecommunications network. Additionally, while the tool, which utilises combined ensemble models, has proven to be more accurate in detecting DR, it demands substantial computing power, a notable challenge in under-resourced countries like Zambia. Moreover, the study involving Ethiopia's healthcare landscape suggested that AI-powered digital health solutions can transform healthcare and societal well-being. However, infrastructure challenges hinder their full adoption and implementation [81].

For AI to flourish in the country, the government should ensure equity in infrastructure developments to minimize the digital divide and implement policies that favor the implementation of AI tools [82]. According to WHO, countries in the WHO African region allocate only 7 % of the government expenditure to infrastructure, including ICT, which falls short compared to 33 % invested by the country with a relatively better-performing health system [83]. The AU's recently released white paper explicitly emphasizes the need for AI infrastructure as one of the key mechanisms to achieve the AU Agenda 2063. The paper suggests that targeted investments in high-performance computing, fast connectivity, and data storage systems are essential to support the deployment of AI solutions [17]. Notably, strengthening financing and health infrastructure is critical for African countries to achieve Universal Health Coverage (UHC) [84].

4.3. Skills and talents

The major obstacle to AI adoption in both the public and private sectors is the limited skills and awareness of AI among the workforce [38,39,85]. The skills gap is due to various factors, including a shortage of AI-ready workers, inadequate education and training programs, and a lack of awareness about the benefits of AI [68]. It is worth noting that different players in the AI ecosystem require different levels of skills, from technical to foundational and enabling skills. Investing in robust education and training programs focused on AI and data science can help equip youngsters, healthcare professionals, and researchers with the necessary skills to effectively develop, implement, and use AI-driven solutions within the healthcare system. These programs should encompass critical areas such as data science, machine learning, deep learning, and software engineering, enabling the sector to harness the transformative power of AI [12]. Software Engineering (SE) is often regarded as a gateway skillset to AI development and a key indicator of the availability and supply of AI talent. However, reports indicate that SE professionals are scarcer in Africa than in other regions globally. For example, Israel has 9.5 times more software engineering professionals per capita than South Africa, 40 times more than Nigeria, and 170 times more than Ethiopia [86].

The successful implementation of AI in clinical environments necessitates a skilled workforce that can develop, maintain, and utilize AI systems effectively. However, many African countries struggle with a lack of AI experts, consequently hindering the adoption of AI-driven solutions [87]. Akingbola et al. [34] highlight the necessity of building local expertise to advance AI applications in oncology in Africa. They advocate for establishing training programs to develop healthcare professionals' skills alongside AI specialists. Similarly, Manson et al. [37] suggest that African countries need to invest in skills development to accelerate the integration of AI technology into radiotherapy practices.

The public sector is well-positioned to leverage AI across various sectors, including healthcare. Yet, this potential remains largely unrealized due to inadequate internal capacity and expertise within government agencies [86]. Government AI Centers of Excellence can serve as a driving force for innovation and capacity development in the public sector, simultaneously creating valuable career opportunities for highly skilled professionals [86,40]. Moreover, it is crucial to prioritize digital literacy by equipping the younger generation with foundational skills beginning from primary education. This early focus will empower students with the competencies to navigate and succeed in an increasingly digitally interconnected world. For instance, currently, only half of African countries include computer skills in their school curriculum, compared to a global average of 85 % [88]. The AU aspires that by 2033, a minimum of 80 % of children complete primary education with the essential proficiency levels in digital skills [89]. To prepare the workforce for the demands of an increasingly evolving digital landscape, some African countries have started taking action to revamp their education curricula. For example, in Tanzania, recent enhancements to the primary education curriculum emphasize ICT skills as a core competency for students. Students are expected to gain proficiency in using ICT tools and systems and to demonstrate the ability to design basic computer programs [90]. In 2021, Ghana also introduced a new national computing curriculum for junior high schools that covers the aspects of programming, robotics and AI [91]. Moreover, between 2020 and 2022, South Africa has been piloting its new coding and robotics curriculum at different levels of primary education [92]. This, however, should be accompanied by strengthening the capacity of higher education institutions to offer AI-focused programs and conduct advanced research, equipping graduates with the specialized skills needed in this field. A recent review of AI capacity building in sub-Saharan Africa revealed gaps in AI expertise and faculty, as well as limited capacity for enrolling and supervising graduate students [85]. In part, these challenges could be mitigated by establishing joint academic programs with other higher education and training centers, supported by partnerships with industry or government entities [85].

4.4. AI regulation and policy development

In light of the risks associated with AI in healthcare, establishing mechanisms to regulate its responsible deployment is essential [57]. AI-driven healthcare systems, while transformative, may inherently cause biases and threaten patients' privacy [93]. A recent study evaluating the acceptability of an AI-assisted tool for diagnosing cervical cancer among women in Cameroon revealed that its acceptance largely depends on ensuring the privacy and confidentiality of patient information [55]. Thus, public sector involvement is critical to govern AI's ethical use in healthcare. The multifaceted nature of the health sector demands a comprehensive approach in which the government plays a central role in developing and enforcing policies and regulations that uphold ethical standards, protect patient privacy, and promote transparency. This approach aligns with the European Parliament's recently published report on Artificial Intelligence in Healthcare [94] and Rwanda's newly adopted National AI Policy [95]. While regions like the European Union and North America have established comprehensive AI frameworks emphasizing ethics, data protection, accountability, and regulation, such as the European Union AI Act, most African countries are still in the early stages of policy formulation. Africa's AI initiatives often focus on capacity building, digital infrastructure, and leveraging AI for socio-economic development, with fewer formalized legal frameworks. However, regional bodies like the African Union have begun to advocate for a continental AI strategy that aligns with global standards while addressing Africa-specific challenges such as digital inequality, limited data governance, and infrastructural gaps. This contrast highlights both the global disparity in AI governance and the growing momentum within Africa to shape contextually relevant AI policies.

It is worth noting that addressing barriers to digital healthcare acceptance requires developing and implementing targeted health policies at all levels of healthcare delivery. These policies should be customized to align with the sociocultural norms and practices of the communities using these digital healthcare tools [96]. Similarly, AI in healthcare should be governed by guidelines prioritizing patient and community well-being, ensuring that care is delivered ethically and equitably [97]. Bottomley and Thaldar [56] suggest that adopting AI in Africa's healthcare is not just a scientific or medical shift - it also calls for legal reflection and adaptation. For example, Ghana and Kenya are emerging leaders in AI-driven healthcare innovation, each following distinct pathways shaped by policy frameworks and local partnerships. In Ghana, the Health Community of West Africa (HCOWA), alongside Ghana Health Service, is developing a regional AI-powered disease surveillance framework that integrates environmental and health data to predict outbreaks such as malaria and cholera [98]. In contrast, Kenya has embraced AI within a more mature digital-health ecosystem, embedding AI into its national digital master plan as one of the key technologies in delivering Smart Health and deploying private-sector-led tools at scale. For instance, a maternal-and-child health platform like "PROMPTS" by Jacaranda Health is an AI-enabled tool delivering real-time maternal health advice. The tool has also been tested in Ghana to check its feasibility and effectiveness. The goal is to support the government priorities in maternal and neonatal health.

According to Distor et al. [99], in Rwanda, AI tools have been proposed to minimize diagnostic errors caused by the limited number of doctors managing large patient loads. Similarly, Tanzania's Afya Intelligence Solutions provides a chatbot that connects suppliers with pharmacies and allows users to consult virtual doctors for disease predictions and advice. However, the adoption of these technologies is hampered by a lack of regulations governing AI in healthcare [99]. For instance, in South Africa, Donnelly [58] argues that the latest digital health policy strategy adopts the WHO definition of digital health, paving the way for AI integration in healthcare to achieve its strategic objectives. However, the policy and existing regulatory policy environment fall short of providing clear principles to guide the development and deployment of AI. For example, the study explores critical areas for legal reform concerning AI in healthcare and suggests that existing regulatory frameworks for overseeing software as a medical device should be updated to effectively govern the use of these emerging technologies. Moreover, despite the well-known risks of AI in healthcare, its use is not governed by sui generis legislation specific to AI [100]. For instance, a study analyzing the digital health strategies of 42 African countries revealed that only two have implemented comprehensive security and privacy policies within their healthcare digital transformation initiatives [101]. Besides, as AI research and implementation progress, it is essential to develop guidelines that evaluate AI's moral status and ensure its advancement aligns with the values of African societies [102].

The WHO ethics and governance of AI for health guidance suggests that policies, laws, and principles for regulating and managing the use of AI for healthcare are limited and fragmented [103]. An analysis of 12 African countries highlights a fragmented AI regulatory landscape, underscoring the importance of advancing regulatory frameworks to prepare Africa for future AI adoption in healthcare [104]. According to the AU Continental Artificial Intelligence Strategy 2024 [38] six African countries: Mauritius, Senegal, Benin, Algeria, Rwanda, and Egypt, have already developed AI strategies. Each strategy emphasizes different aspects that aim to promote and govern AI in the country. Such aspects include establishing AI centres of excellence, national data infrastructure, AI governance, partnerships, and capacity building. Other African countries are making progress in defining AI policies and setting up institutions to spearhead AI development [38]. For example, in 2022, Tanzania launched its first policy framework for Artificial Intelligence in the health sector. It outlines key aspects to guide the implementation and use of AI in the health sector [105]. These initiatives lay a strong foundation for establishing a supportive regulatory framework, creating an environment where AI can thrive and drive transformative advancements in healthcare.

4.5. Funding

Funding is a cornerstone in accelerating AI uptake across Africa, where challenges in financial resources contribute to the slow pace of progress. Reports indicate an increase in financing for technology initiatives across Africa in recent years, with South Africa, Kenya, Egypt, and Nigeria accounting for a substantial share of the funding [106]. However, on a global scale, the region still lags behind in Venture Capital (VC) investments in AI. For example, Fig. 2 highlights this disparity, based on recent OECD (Organisation for Economic Co-operation and Development) data on VC investments in AI within healthcare, drugs, and biotechnology [107]. In 2024, for instance, the total VC invested in AI for healthcare in South Africa, Kenya, and Nigeria amounted to just 0.05 % and 0.25 % of the corresponding investments in the United States and China, respectively. Limited public investment in AI research, infrastructure, and capacity building has constrained the development and implementation of AI solutions [39]. The AfriLabs report [108] reveals that Africa is home to over 2400 AI companies, 41 % of which are startups. Limited funding and government support have been mentioned on the list of challenges facing AI startups that are considered to have great opportunities for the African market. For example, Webpack and Xavier Africa in Eswatini and Botswana, respectively [108]. Moreover, several other studies also suggest that insufficient funding is among the barriers to the adoption of AI, for example, in radiotherapy practice [37] and medical imaging [70]. Despite promising initiatives like the AU's Digital Transformation Strategy for Africa 2020–2030 [109] and the AU Agenda 2063 [89], which encourage investment in digital and AI-related projects, financial commitments are often insufficient to meet growing demands. In response to the latter, there have been notable initiatives from the private sector aimed at addressing research funding challenges. In 2018, Google Research launched Africa's first AI Research Center in Ghana and committed to opening a new product development center in Nairobi [110]. And recently, it pledged $5.8 million to advance AI skilling initiatives across Sub-Saharan Africa [111]. In 2013, IBM Research launched its first lab in Kenya, and three years later, it launched the second one in South Africa. Similarly, partnerships like the Artificial Intelligence for Development in Africa (AI4D) program funded by IDRC (Canada's International Development Research Centre) and Sida (Swedish International Development Cooperation Agency) have shown how targeted funding can enhance AI innovation and capacity building. One notable initiative funded by these organizations is the AfriAI Lab, hosted at the University of Dodoma in Tanzania. The lab has contributed to advancing AI-driven healthcare solutions and providing essential resources, including computing power, to support AI research and innovation. These efforts demonstrate that external funding from the private sector and development partners can accelerate AI adoption when strategically aligned with local priorities.

On the other hand, African governments have shown commitment to boosting investment in AI through different mechanisms, including government funding and attracting local and foreign investment. However, based on the statistics on global investment in R&D, the region's investment is still low [112]. Despite ongoing efforts, governments must take proactive steps to allocate resources for AI research grants and offer tax incentives to foster AI-driven innovation. Strengthening multilateral collaboration and leveraging funding through development banks and global AI funds could also help address financial gaps while ensuring AI adoption aligns with national development goals. The recent United Nations Development Programme (UNDP) report [113] suggests that African governments should create technology-friendly economic policies to foster domestic AI talent, fund AI research, and invest in AI education and training to cultivate future African AI leaders. Similarly, AU insists that while global investment remains crucial, the foundation

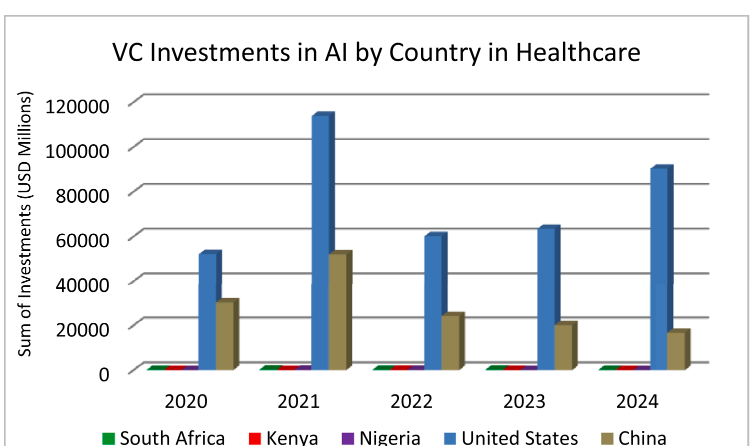

Fig. 2. VC Investments in AI by country in healthcare [107].

of AI development in Africa should rest on investments by African governments and the continent's private sector to ensure sovereign AI capabilities [38].

4.6. Partnerships

Collaborative efforts between government bodies, healthcare institutions, and tech companies can foster an ecosystem where AI innovations thrive, driving sustainable improvements in healthcare delivery. Strengthening regional partnerships is essential for establishing cross-border data-sharing frameworks, granting broader access to public sector data. This collective data resource can support local AI developers in driving innovation and addressing critical development goals [114]. Moreover, partnerships among policymakers, universities, startups, large companies, and multi-stakeholder groups are vital for accelerating AI in Africa. These key actors of the AI ecosystem contribute to fostering innovation, enhancing skill development, and cultivating an environment that supports the successful integration of AI across various sectors [39]. The report by Ibeneme et al. [115] suggests that strategic partnership among governments, academia and the private sector is fundamental in accelerating AI deployment in Africa. The report emphasized that collaborative partnerships are essential for tackling global health challenges, advancing digital health, and enhancing AI-powered healthcare services delivery across Africa [115]. In the radiotherapy practice, for example, Manson et al. [37] posit that the collaboration between African institutions, radiotherapy departments,

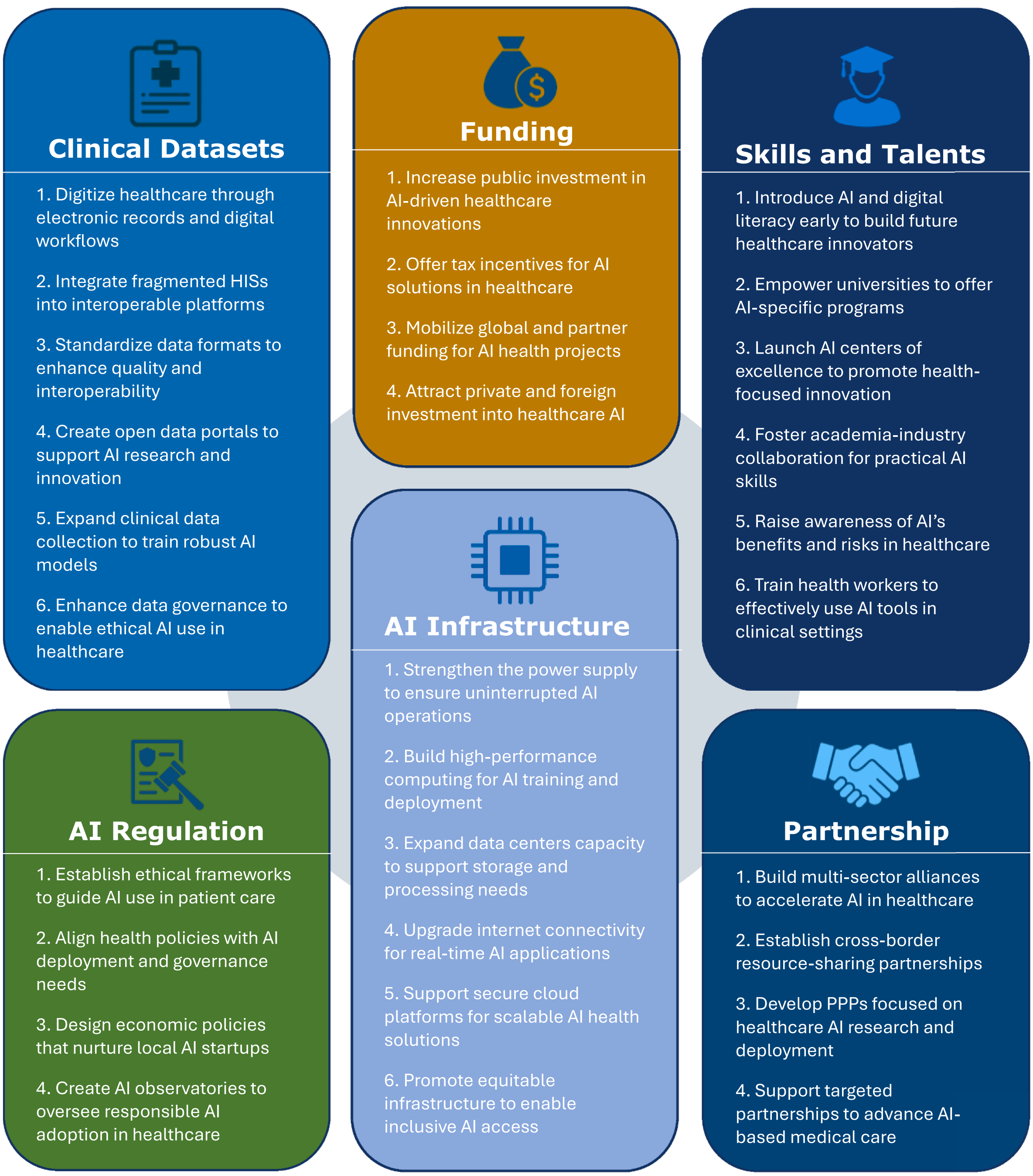

Fig. 3. Recommended action items for improving AI adoption.

and key stakeholders can help build the capacity of radiotherapists in using AI-driven therapeutic technologies. One notable example of the Public-Private Partnership (PPP) is Tanzania's government-led Data Use Partnership (DUP) initiative with the goal of enhancing the national healthcare system by optimizing the use of health information [116]. The initiative has achieved notable milestones, including streamlining the implementation of digital health and data systems and advancing the digitalization of primary healthcare. The PPPs in Africa are prevalent and present a good opportunity for the growth of the health sector. Mugwagwa and Banda outline examples of the PPPs in Southern African countries [117]. However, deliberate efforts are needed to establish PPPs purposely to enhance research and innovation [118].

4.7. Discussion

Africa's journey in AI shall not necessarily mirror that of other regions. The continent can chart its own path, building AI systems that are not only technologically advanced but also equitable, sustainable, and locally transformative. Africa occupies a distinctive position in the global AI ecosystem, marked by both constraints and untapped opportunities that could support transformative AI adoption, particularly within public sector domains such as healthcare. Fig. 3 summarizes recommended action items that can be considered by the public sector to accelerate AI adoption in healthcare. It is worth noting that these recommendations can be generalized to serve other sectors as well. While leading economies like the United States and China dominate through mature industries, expansive infrastructure, and deep research ecosystems, Africa's comparative advantage lies in its youthful population, policy flexibility, and culture of grassroots innovation. It is projected that by 2030, young Africans will constitute 42 % of the global youth population. With over 60 % of its population under the age of 25, the continent has the potential to develop a robust, future-ready AI workforce through investment in digital education, technical skills training, and innovation hubs. Although most African countries are in the early stages of AI policy development, this policy infancy provides a clean slate to craft agile, inclusive, and context-sensitive governance frameworks, drawing lessons from both over-regulated and under-regulated environments globally. Infrastructure gaps remain a challenge, yet Africa has already demonstrated the capacity to leapfrog traditional development models through mobile banking and digital innovation. Scalable technologies such as cloud computing and open-source platforms offer further promise. Additionally, the continent's demographic trends, urbanization, and public sector needs position it as a natural testbed for frugal, high-impact AI applications that prioritize social equity. Unique to Africa is a bottom-up innovation dynamic, where local relevance and necessity-driven solutions emerge from community-level experimentation. These conditions create a pathway for Africa to not only adopt AI but to shape a distinct, socially grounded trajectory that contrasts with the commercially driven models prevalent elsewhere.

The power dynamics surrounding AI adoption in African healthcare reveal a growing imbalance between public institutions and private, often foreign, driven largely by reliance on donor-led technologies. While donor agencies and international tech firms have accelerated innovation, they often monopolize essential infrastructure, data pipelines, and algorithmic development, fostering dependencies that restrict national sovereignty and local agency. This means African nations are not only adopting tools but also importing external governance models that may not align with local contexts or societal values. In a typical case, the external storage and processing of health data beyond national jurisdictions further limit the capacity of governments to oversee, regulate, or ensure alignment with national data governance frameworks. Proprietary systems exacerbate this issue by operating as black boxes, rendering their logic inaccessible and impeding transparency and accountability in public health decisions. In light of these challenges, scholars and practitioners are calling for the development of Afrocentric AI governance rooted in indigenous ethical frameworks such as Ubuntu, which prioritize community, fairness, and inclusive decision-making. Without such sovereign, locally grounded approaches, Africa risks reinforcing patterns of digital dependency and inequality, rather than building AI systems that are equitable, sustainable, and responsive to its unique healthcare needs.

In summary, this study highlights the public sector's often-overlooked yet central role in accelerating AI-driven healthcare transformation in Africa by framing its "hidden strengths" as untapped assets. These include existing health information systems such as DHIS2, which collect valuable longitudinal data across public health facilities and could serve as foundational inputs for AI models. Public research institutions and universities possess technical expertise and can anchor interdisciplinary innovation if better supported and integrated into AI ecosystems. In addition, many African governments have led or co-managed pilot projects—such as predictive models for maternal health or malaria surveillance—often in partnership with donors, but these efforts are rarely scaled or systematically leveraged. The public sector also holds regulatory authority to shape ethical AI deployment through data governance and has a unique level of public trust that can facilitate technology uptake, particularly in underserved areas. By illuminating these underrecognized capacities, this study reframes the public sector not as a passive recipient of AI innovation but as a key actor with institutional and infrastructural leverage to lead responsible and inclusive AI adoption in healthcare.

5. Conclusion

This paper highlights the pivotal role of the public sector in accelerating AI adoption to transform healthcare in Africa. By addressing critical barriers such as limited funding, insufficient skills, data accessibility challenges, and inadequate infrastructure, the public sector can establish a solid foundation for a thriving AI ecosystem. Existing initiatives, including inclusive policy frameworks, capacity-building programs, and innovative public-private partnerships, provide valuable entry points for scaling AI-driven healthcare solutions across the continent. Strategic leadership from the public sector is essential to integrate AI into healthcare systems effectively, fostering innovations in diagnostics, predictive analytics, and personalized care. These efforts address healthcare gaps and align with broader digital transformation and sustainable development goals, particularly SDG 3 on good health and well-being. By capitalizing on existing momentum, mobilizing financial and technical resources, and fostering collaboration among diverse stakeholders, the public sector can ensure that AI is harnessed to create equitable, efficient, and resilient healthcare systems. However, to enable the effective deployment of AI in resource-limited healthcare settings, it is necessary to prioritize cost-effective, scalable solutions that are contextually relevant and address pressing local health challenges. This includes investing in foundational digital infrastructure, such as electronic health records and computing resources, as well as comprehensive workforce development initiatives to build local AI and data literacy. Establishing robust ethical and regulatory frameworks is equally vital to safeguard patient data, ensure transparency, and promote algorithmic fairness. Additionally, fostering strategic public-private partnerships can catalyze innovation by supporting pilot programs that test and refine AI tools in real-world clinical environments, ultimately informing broader policy and scaling strategies. Besides, we note that to support responsible AI adoption in African healthcare systems, research and innovation should prioritize co-creation with local stakeholders and leverage approaches that address infrastructural constraints. Governments may consider supporting small-scale pilot programs on high-impact areas like maternal health, diagnostics for endemic diseases (e.g., Malaria and Tuberculosis), or supply chain optimization. These pilots should incorporate evaluation frameworks to measure effectiveness, equity, and ethical implications. On the policy side, governments can establish multi-sectoral AI-for-health task forces, invest in capacity-building for regulators, and develop adaptive guidelines for AI validation and deployment. Finally, fostering regional collaboration through platforms such as the Africa CDC and the African Union can facilitate harmonized policies, cross-border knowledge exchange, and a collective vision for responsible AI deployment.

While this scoping review provides a foundational understanding of the current discourse and highlights the underexplored role of the public sector in AI-driven healthcare transformation in Africa, future research should build on these insights through empirical investigation. Specifically, studies incorporating stakeholder interviews, surveys, or in-depth case studies would offer valuable, context-specific perspectives and help validate or challenge the themes identified in this review. Such empirical work helps capture the lived experiences, institutional dynamics, and policy considerations that shape the deployment of AI in public health systems across the continent.

CRediT authorship contribution statement

Ally S. Nyamawe: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

Authors declare no competing interests.

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Data availability

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

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