

**Individual Research Paper on  
Enabling Conditions for Health AI R&D in Africa**

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### Acrynomns List:

1. **AI** – Artificial Intelligence
2. **R&D** – Research and Development
3. **IDRC** – International Development Research Centre
4. **ICT** – Information and Communication Technology (used here in “Kenya Ministry of ICT”)
5. **UNESCO** – United Nations Educational, Scientific and Cultural Organization
6. **SSA** – Sub-Saharan Africa
7. **TB** – Tuberculosis
8. **KII / KIIs** – Key Informant Interview(s)
9. **FGD / FGDs** – Focus Group Discussion(s)
10. **NGO / NGOs** – Non-Governmental Organization(s)

## **Section 1: Introduction**

### **1.1 Research Question and Thesis**

Artificial intelligence (AI) is increasingly portrayed as a transformative tool capable of addressing persistent global health challenges across a range of healthcare settings (Zuhair et al., 2024). Yet this narrative often hides the uneven outcomes of AI innovation, and how these outcomes are shaped by inconsistent functional capacities between states. With that in mind, the research question this paper asks is: “How do challenges around enabling conditions prevent a conducive environment for AI and health research and development (R&D) in Africa?”

Consequently, this paper’s thesis argues that “challenges tied to infrastructure, regulation, funding, and skills capacity are among the most prominent barriers that need to be overcome in order to build a conducive environment for health AI R&D in Africa. Moreover, for this R&D to be successful, it requires dedicated attention to African value systems, rather than relying solely on broad, generalized ethical principles.”

This paper has five main sections. Section 1 (this section) discusses the research question, thesis, connection to broader group project, definitions, and limitations. Next, section 2 explains the search strategy for the literature review. Section 3 is the thematic literature review, and it analyzes evidence around enabling conditions, trust & ethics and then applies these two themes specifically to the context of health in the final theme. Section 4 examines policy responses, focusing on Kenya. Finally, section 5 concludes with a reiteration of how this paper has answered its research question and proven its thesis.

### **1.2 Connection to Broader Group Project**

The broader group project question asks: “What are the gaps in research agendas and protocols, and the ‘siloization’ of AI and global health research, that hinder the alignment of global health goals with AI technologies?”

While this paper does not map gaps in research agenda or protocol designs specifically, what it does seek to do is complement the group research question by examining the pre-conditions that must exist for those agendas and protocols to be successful in the first place. This paper will show that even the best-designed healthcare AI research agendas and protocols will struggle if they are trying to build in an environment lacking certain important preconditions. As a group, we have chosen Africa as our region of study, thus this paper’s contribution will be to provide the foundational landscape for the group’s overall research.

### 1.3 Key Definitions

Before proceeding further, it is important to set down the definitional understandings for some of the key terms explored throughout this paper, starting with AI.

#### *Artificial Intelligence (AI)*

According to Ulnicane et al. (2021), AI can be understood as an umbrella concept rather than a definitively defined technology. As they note, “there is no single accepted and rigid definition of AI. AI is a catch-all term for a large number of sub(fields) such as: cognitive computing ... machine-learning ... augmented intelligence ... and AI robotics” (EESC, 2017, as cited in Ulnicane et al., 2021, p. 159). Different actors define the term differently. As an example, Kenya’s National AI Strategy defines AI as “a collection of emerging technologies that leverage machine learning, data processing, and algorithmic systems to perform tasks that typically require human intelligence... including automated decision-making, language processing, and computer vision” (Kenya Ministry of ICT, 2025, p. 15).

#### *Enabling Conditions*

For the purposes of this paper, “enabling conditions for AI” refer to “the necessary elements for [AI] to be developed, deployed, and used effectively and responsibly” (Google, 2025). This paper specifically narrows the scope on four key enabling conditions: physical and digital infrastructure; data ecosystems; regulatory frameworks; and funding and skills.

#### *Responsible AI*

There is no single, universal definition of “Responsible AI,” however, several scholars and institutional sources provide their own definition. For example, the International Development Research Centre (IDRC) describes “Responsible AI” as AI that is safe, inclusive, rights-based, ethical, and sustainable (IDRC, n.d.). According to Eke et al. (2023) the dominant “Responsible AI” definitions originate from the Global North. They echo the calls of other scholars to “reconceptualize the notion of responsible innovation... [because it has] been developed in the Global North with little reference to what [“responsible”] may mean in the Global South” (Wakunuma et al., 2021, as cited in Eke et al., 2023, pp. 3–4).

### 1.4 Limitations and Acknowledgements

There are some broad limitations associated with this paper that require acknowledgement before proceeding:

**Africa’s diversity:** Africa is a highly diverse continent with a multitude of political systems, histories, cultures, and governance styles. It is not a monolith, yet this paper often discusses the continent of Africa as a whole (without distinguishing between countries and

societies). The limitation of this approach is that it overlooks, and may even downplay, important country-specific nuances. Despite this limitation, this approach was deemed appropriate to take as much of the literature reviewed also takes either a continental or sub-regional approach to geographic scope. Regardless, to mitigate, I have tried to mention the specific country when it was clearly mentioned in the article being studied.

**Focus on gaps and challenges:** Because this paper is explicitly about gaps and challenges in enabling conditions for AI, it may appear as if the paper is painting an overly negative view for AI R&D in Africa. This should not be interpreted as suggesting that the continent lacks strength, innovation, or world-class contributions in the AI space. In fact, much of the literature highlights the highly technical, creative, and successful AI contributions being pursued across the region. The relative absence of these success stories in this paper should not be seen as a negative or biased stance toward Africa's AI ecosystem, rather just as a reflection of the research question asked.

## Section 2: Search Strategy

The last item to cover before jumping into the actual analysis is this paper's search strategy. Before starting the record search for this project, a table of article type, methodology, geographic scope, and time frame was established to guide the research strategy (refer to Table 1 below). Peer-reviewed journal articles, commentaries, editorials, blogs, statements, reports, news articles, national policies and their related draft documents were all included, whereas Wikipedia articles were excluded. The scope of these documents covered both quantitative and qualitative studies with a global geographic focus when researching general criteria (such as "AI framing"), and specific searches for the African continent and Kenya when researching specific criteria (such as national policies).

Finally, the time frame from which studies were included was 2018 onwards. 2018 was selected because that was when the first National AI Policy was released on the African continent (from Mauritius). Selecting a 7-year time frame (2018 to present) also ensured that the research would be as relevant and up-to-date for a field of study that has seen significant technological advances year-to-year.

**Table 1**

*Inclusion and exclusion criteria table developed to guide the paper's search strategy*

	Included	Excluded
Article Type	<ul style="list-style-type: none"> <li>• Peer reviewed journal articles, commentaries, editorials, blogs, statements, reports, news articles, national policies, and their related draft documents.</li> </ul>	<ul style="list-style-type: none"> <li>• Wikipedia</li> </ul>
Methodology	<ul style="list-style-type: none"> <li>• Quantitative Studies</li> <li>• Qualitative Studies</li> </ul>	
Geographic Scope	<ul style="list-style-type: none"> <li>• Global but with specific searches just for African Continent and Kenya.</li> </ul>	
Time Frame	<ul style="list-style-type: none"> <li>• 2018 to present</li> </ul>	<ul style="list-style-type: none"> <li>• Pre-2018</li> </ul>

To investigate the research question, records were identified both through a database search and manual searching. Five databases were searched to identify records – Google Scholar, Biomed Central, PubMed, Scopus, and ScienceDirect – and they yielded a total of 79 records combined. Similarly, manual searches were conducted on Google for specific African AI policies, related documents, IDRC's "Responsible AI" definition, and for articles or relevance identified from another article's reference list. This process yielded a total of 21 records combined. All in all, the research process yielded 100 potentially-relevant records.

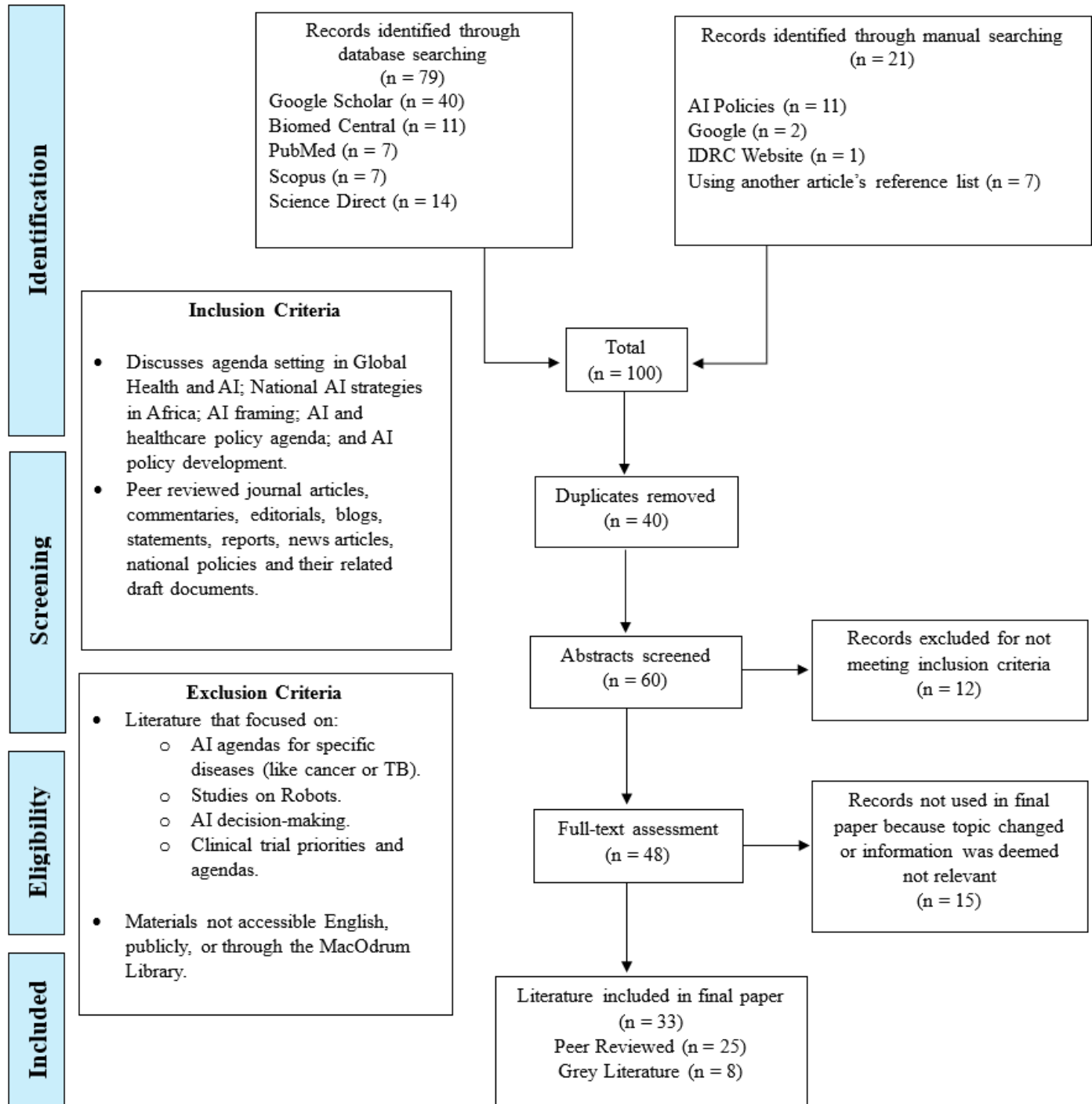
Certain search terms were included and excluded. When looking at excluded terms specifically, these were: AI agendas for specific diseases (like cancer or TB); Studies on Robots; AI decision-making; Clinical trial priorities and agendas. It was found that any search including the term "agenda" brought forth a range of article titles that did not match the requirements (such as agendas for specific conferences or meetings). For a detailed breakdown of the included terms, please consult the Appendix of this paper which provides the: search terms used; date of search; database used; total articles found; and total articles downloaded and reviewed.

As you will note in Figure 1 below, 40 duplicates were removed, and 60 abstracts were screened – of which 12 did not meet the inclusion criteria. Once that was done, 48 records remained which were all either fully assessed (full text read) or partially assessed (Introduction, Findings and/or Conclusion read). All in all, 33 records ended up being used in the writing of this paper and 15 were read but not used (because the topic covered in the final paper changed or the information was deemed ultimately not relevant). From the 33 records cited, only 25 were peer-reviewed and the remaining 8 were grey literature. Overall, the literature reviewed was a

combination of peer reviewed and grey literature, with many of the grey literature pieces appearing via formal journals, policy organizations, or official country websites.

**Figure 1**

*Search results decision-tree*



## Section 3: Analysis of Evidence Base

### 3.1 Theme 1: Africa's Enabling Conditions

The consistent emergent theme across the literature on AI in Africa is the necessity of having certain enabling conditions in place in order to responsibly advance AI R&D. These include stable physical and digital capacities, strong data and regulatory ecosystems, and funding and skill considerations (Ade-Ibijola and Okonkwo, 2023; Diallo et al., 2025; Gwagwa et al., 2020; Jaldi, 2023; Kiemde and Kora, 2020; Mienye et al., 2024; Okolo et al., 2023; Sibal and Neupane, 2021; Townsend et al., 2023).

#### *Physical and Digital Capacity*

A major barrier highlighted across the literature is the limited physical and digital infrastructure needed to support AI development in Africa (Gaffley et al., 2022; Jaldi, 2023; Kiemde & Kora, 2020; Okolo et al., 2023). AI-enabling systems like data centres rely on large broadband networks and storage systems which require huge amounts of electricity to run (Kiemde & Kora, 2020). Yet more than 630 million people in Africa – mostly in Sub-Saharan Africa – still lack reliable electricity (Jaldi, 2023). These challenges are even more acute in rural areas where only 28% of people in Sub-Saharan Africa have access to electricity, compared to about 80% in urban areas (Okolo et al., 2023). Given the limits of electricity, internet access also shows similar gaps. Africa has some of the lowest broadband coverage in the world (Kiemde and Kora, 2020). These connectivity gaps make it difficult to effectively develop and deploy AI. Network expansion will require more investment from states in fibre-optic cables and towers, the removal of structural barriers such as high taxes and high licensing fees in order to succeed (Kiemde & Kora, 2020).

#### *Data Ecosystem*

Another major challenge for AI development in Africa relates to data. Machine-learning depends on large, high-quality datasets, yet African data is often scarce, undigitized, or expensive to access (Kiemde & Kora, 2020; Owoyemi et al., 2020). The quality and representativeness of the available data can also be a challenge (Kiemde and Kora, 2020; Pasipamire and Muroyiwa, 2024). Consider an example from the financial sector – the rate of banking is low in Sub-Saharan Africa with low-income marginalized communities having fewer bank accounts (Kiemde and Kora, 2020). Thus, when banking data is used to create AI algorithms, they may systematically exclude low-income and marginalized communities (Kiemde & Kora, 2020). Moreover, what counts as “representative” data may also be context dependent. For example, Okolo et al., (2023) notes that “in regions where the social construct of race is not present, focusing solely on the lack of racial representation in datasets limits how people address other facets of dataset underrepresentation [such as] ... ethnicity, tribal affiliations and other cultural nuances” (p. 46).

#### *Regulatory Ecosystem*



Another major enabling condition is the strength and coherence of “AI-adjacent” regulations. Essentially, developing responsible AI systems requires far more than just AI-specific policies (Gaffley et al., 2022; Balogun et al., 2023; Townsend et al., 2023). As the previous section has shown, AI is inseparable from data-related challenges, meaning it is also inseparable from data-related regulations (Gikunda and Kute, 2023; Townsend et al., 2023). Weak cybersecurity and data protection laws create risks related to data collection, ownership, anonymity, and consent (Oladipo et al., 2024; Townsend et al., 2023). Beyond data governance, laws also need to exist in areas such as consumer protection and product liability (Townsend et al., 2023). Since AI technologies introduce new types of risk, having robust and adaptable legal regimes about who should be held liable if a technology produces harm is important (Townsend et al., 2023). Similarly, intellectual property regulations are also foundational as copyright and patent laws shape how AI-enabled products are created, shared, and sold (Townsend et al., 2023).

In 2021, UNESCO surveyed 32 of its member states<sup>1</sup> in Africa on what states identified as their priorities and capacity-building needs with respect to AI (Sibal and Neupane, 2021). Among the top results was the need for stronger legal and regulatory frameworks to manage AI (Sibal and Neupane, 2021). While many states have adopted data protection laws, these may require updating to address algorithmic bias, discrimination (such as race and gender bias), and the privacy risks that predictive analytics brings about (Sibal and Neupane, 2021).

### ***Capacity and Skills Acquisition***

The final enabling capacity to be discussed relates to funding capacity and skills acquisition. Along with other enabling conditions like physical, digital, data, and regulatory capacity, advanced technologies also require sustained monetary investment. Yet many governments on the continent continue to struggle with basic revenue generation, leaving limited funding for AI-related capacity building (Onyango, 2024). Additionally, at the technical level, AI development requires specialized education and work experience in programming, machine learning, and natural language processing – skills that remain in short supply across the continent (Gikunda and Kute, 2023; Ade-Ibijola & Okonkwo, 2023; Eke and Ogoh, 2023).

### ***Conclusion***

Overall, the literature demonstrates that Africa’s AI advancement needs to go hand-in-hand with foundational enabling conditions like physical, digital, and funding investments, strong data and regulatory ecosystems, and training of skilled professionals. This is by no means an exhaustive list; rather it reflects some of the most persistent challenges identified across the literature.

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<sup>1</sup> The 32 countries surveyed were Angola, Benin, Botswana, Cabo Verde, Cameroon, Chat, Comoros, Congo, Ivory Coast, Democratic Republic of Congo, Egypt, Equatorial Guinea, Eswatini, Gambia, Ghana, Guinea, Lesotho, Madagascar, Malawi, Namibia, Nigeria, Rwanda, Sao Tome and Principle, Senegal, Seychelles, Sierra Leone, Somalia, Sudan, Togo, Uganda, Zambia, and Zimbabwe.

### **3.2 Theme 2: Trust, Legitimacy, and African & Indigenous Epistemologies**

In addition to enabling conditions, another foundational element that AI R&D must address in order to be successful in African contexts is the elements of trust, legitimacy, culture and ethics (Birhane, 2020; Pasipamire & Muroyiwa, 2024; Salaam et al., 2025). Several African scholars have also identified that for AI to be truly “responsible” and socially acceptable in Africa, it must take into account African value systems and Indigenous epistemologies (Eke & Ogoh, 2022; Eke et al., 2023; Salaam et al., 2025).

#### ***Colonial Histories and Mistrust***

Perceptions of fairness and trust in AI cannot be separated from broader histories of colonialism and technological abuse. Pasipamire and Muroyiwa (2024) argue that historical mistrust of foreign technologies is embedded in a long history of “unequal exchange” wherein Western economies have siphoned African wealth through minerals, labour, and environmentally harmful activities (Aseka, 1993, as cited in Pasipamire & Muroyiwa, 2024). In a similar vein, Birhane (2020) warns that the continued dependence on Western software and infrastructure risks creating an “algorithmic invasion” where local product development is undermined and Africa’s technological dependency on the West is deepened.

Mistrust of AI in Africa can be further reinforced by contemporary day-to-day experiences of algorithmic bias and discrimination (Gwagwa et al., 2020; Pasipamire & Muroyiwa, 2024). For example, Yahaya and Sokatsha (2025) share their personal experience of an online booking system that rejected their debit card when their nationality was set as Nigerian, but accepted the same card when the nationality was changed to British. Another example of biased AI brought up was when “sometime between 2021 and 2022, many Black people in South Africa discovered that when they changed their names on Uber to a white/non-black or ethnic presenting name, the prices of their trips significantly reduced for the same destination” (Yahaya and Sokatsha, 2025, p. 92).

This goes to show how algorithmic discrimination can silently impact the lives of Africans in ways that reproduce racial and economic harms (Yahaya & Sokatsha, 2025). These lived experiences can erode trust and reinforce perceptions that AI is designed for others, not for Africans (Pasipamire & Muroyiwa, 2024).

#### ***Limits of Imported Global AI Ethics***

Against this background of negative historical and contemporary experiences with Western technologies, comes up the challenge of global AI ethics debates staying heavily shaped by non-African perspectives. In a comprehensive review that Jobin et al., (2019) conducted of 84 guidelines on Ethical AI published from around the world, they identified 11 overarching ethical principles: transparency, justice and fairness, non maleficence, responsibility, privacy, beneficence, freedom and autonomy, trust, sustainability, dignity and solidarity. Notably, none of the 84 AI ethics guidelines reviewed by Jobin et al. (2019) were developed in or for African

contexts, pointing to the fact that global AI ethics debates are being shaped without Africa in mind (Eke et al., 2023).

Eke et al., (2023) contend that when AI ethics frameworks developed in the Global North are simply “exported” to Africa, it constitutes a form of “epistemic injustice” – the idea of unfairly discriminating against one’s capacity as a knower (Byskov, 2021, as cited in Eke et al., 2023). This is unfortunate considering Africa has well-established philosophical and cultural traditions that can provide unique perspectives on ethical principles for the research, development, and deployment of AI (Eke et al., 2023).

### ***African Ethical Tradition of “Ubuntu” as a Foundation for Trustworthy AI***

Several scholars call for AI in Africa to be anchored in African ethical principles and Indigenous epistemologies. A consistent example that came up across several readings was the communitarian philosophy of Ubuntu (“I am because we are”) (Dignum 2023; Eke and Ogoh, 2022; Eke et al., 2023; Pasipamire and Muroyiwa, 2024; Salaam et al., 2025). This philosophy can help provide a deeper understanding of what “responsible AI” could mean in African contexts (Eke & Ogoh, 2022; Eke et al., 2023).

To understand this, Dignum (2023) contrasts Ubuntu with dominant Western conceptions of AI which are often rooted in individualistic rational choice theories. “Ubuntu” on the other hand

expresses the deeply-held African ideals of one’s personhood being rooted in one’s interconnectedness with others ... [this] philosophy is essentially relational and defines morally right actions as those that connect, rather than separate ... This does not imply that individual rights are subordinated, but that individuals pursue their own good through pursuing the common good... (Dignum, 2023, pp. 208-209).

If you apply this to AI research and development, the idea would be to reconceptualize AI systems as designed and evaluated by their effects on communal relationships and collective well-being, as opposed to just individual wellbeing (Dignum, 2023).

### ***Conclusion***

Overall, cultural context shapes whether AI is seen as fair, respectful, or even culturally acceptable (Ade-Ibijiola & Okonkwo, 2023; Pasipamire & Muroyiwa, 2024). If AI tools are experienced as biased or not connecting with a society’s cultural values, they are likely to be resisted, even if they comply with global ethical standards.

## **3.3 Theme 3: AI in African Healthcare Systems**

Building on the previous two themes, this section explores how enabling conditions and questions of trust and cultural sensitivity play out specifically in African healthcare. While AI

clearly offers potential for strengthening health systems, the same limitations that shape AI more broadly also shape whether advancement of health AI R&D are feasible, safe, and socially acceptable (Balogun et al., 2023; Eke et al., 2023; Oladipo et al., 2024; Salaam et al., 2025; Townsend et al., 2023).

### ***How Enabling Conditions Manifest Themselves in AI and Healthcare***

The enabling conditions discussed earlier like data ecosystems, infrastructure, skills, and regulation become particularly acute in healthcare. In many African contexts, things like electronic medical records and clinical data are often sparse, poorly digitized, or costly to annotate (Owoyemi et al., 2020). As a result, many health AI tools are trained on non-African datasets, which increases the risk that diagnostic models underperform or wrongly classify African patients. This can be dangerous in areas like imaging or precision medicine where physiological and epidemiological profiles differ from those in high-income settings (Owoyemi et al., 2020).

For regulatory gaps, consider the concept of “liability” under consumer law. In a traditional fault-based legal regime (which most are), it would be assumed that a clinician can reasonably foresee and prevent errors (Townsend et al., 2023). However, with AI, this assumption breaks down when clinicians use non-transparent machine-learning systems whose internal workings are not even fully understood by their developers (Townsend et al., 2023). As Owoyemi et al. (2020) note, there are still no clear rules in many countries about who is responsible when AI-assisted decisions cause harm in clinical care. When combined with under-resourced health systems, these gaps can slow or entirely prevent responsible R&D.

### ***How Contextual Elements Manifest Themselves in AI and Healthcare***

Beyond infrastructure and regulation, healthcare AI in Africa raises deeper questions – whether imported tools, values, and problem framings actually resonate with African health realities. Consider for example that “in a comparative study that examined early breast cancer detection practices between Sub-Saharan Africa (SSA) and high-income countries, Black and Richmond (2019) found that applying what has been ‘successful’ in the West, i.e. Mammograms, to SSA [was] not effective in reducing mortality from breast cancer. A combination of contextual factors, such as a lower age profile, presentation with advanced disease, and limited available treatment options all [suggested] that self-examination and clinical breast examination for early detection methods serve women in SSA better than medical practices designed for their counterparts in high income countries” (Birhane, 2020, pp. 395-396). This example shows that an uncritical “copy-paste” deployment of Western e-health and AI systems risk clashing with local disease burdens and relevant solutions.

Local and cultural contexts also shape whether AI-enabled health tools are perceived as legitimate. Salaam et al. (2025) emphasize that AI must be understood in relation to local languages, social relationships, and traditional healing practices. For example, AI systems that do

not take into account such things as traditional healing practices or the respected role of Elders may be distrusted or underused, regardless of their technical accuracy (Salaam et al., 2025).

### ***Conclusion***

Overall, these examples show that the feasibility and legitimacy of health AI in Africa depend as much on local context as they do on technical capability. Without strong enabling conditions and alignment with cultural practices, even well-designed tools risk underperforming or being rejected. Thus, ensuring responsible health AI requires attention to both systems and societies.

## **Section 4: Analysis Of Policy Response**

### **4.1 How Various Policy Organizations Are Addressing the Issue**

This section of the paper is supposed to explore how policy organizations are addressing the issues brought forth thus far. This paper has chosen to analyze “the state” as its “policy organization.” The state level of analysis made the most sense as national governments hold the formal authority to set legal standards, set enabling infrastructure, and define strategic priorities.

Kenya was chosen as the country of study. Kenya’s guiding vision for AI is to become “a regional leader in AI R&D, innovation and commercialization for inclusive socio-economic development” (Kenya Ministry of ICT, 2025, p. 84). The rationale behind the case selection includes:

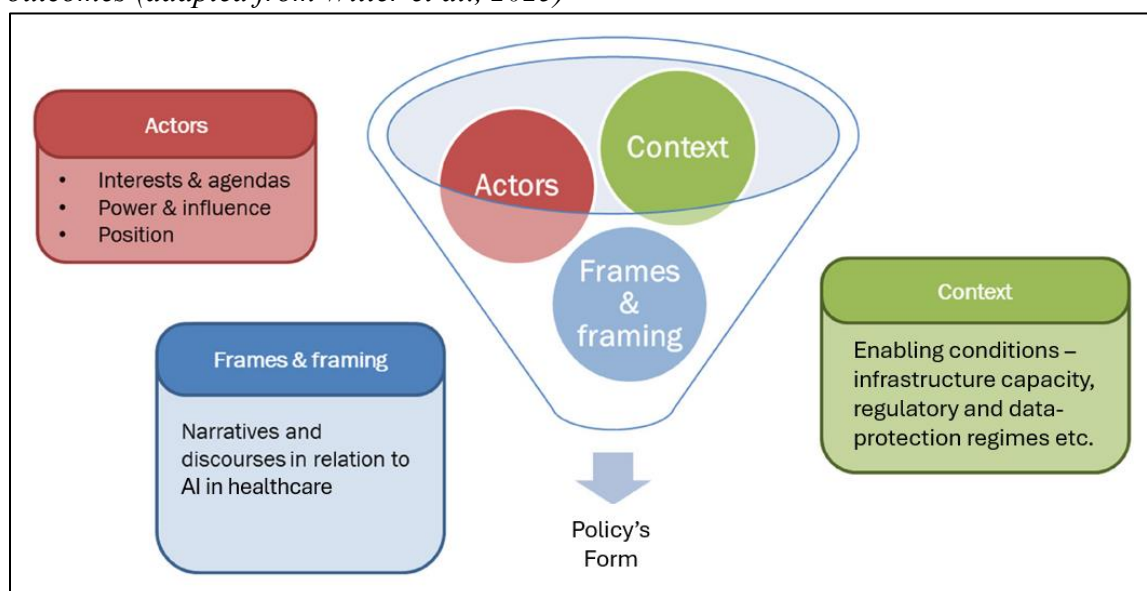
1. **Recency of policy:** Kenya’s national AI strategy was released in March 2025 (Muchiri, 2025), thus providing one of the most recent and time-relevant examples in Africa.
2. **Depth of policy:** The policy is one of the most extensive in its transparency in terms of how it was formulated (methodology), who was at the table (actors), and what factors were given most weight (priority themes and interests).
3. **Availability of literature:** Kenya was also the country with some of the most available literature in terms of AI R&D both generally and in health.
4. **Connection to IDRC:** One of IDRC’s regional offices is in Nairobi, Kenya where the organization has deep ties. Moreover, the IDRC was thanked at the outset of Kenya’s AI policy document as being one of the foreign government partners that supported in the policy process.

### **4.2 Methodology**

The policy will be studied using a political-economy framework of Actors, Context, and Framing (introduced in Witter et al., 2025).

**Figure 2**

*Political economy framework illustrating how actors, context, and framing shape policy outcomes (adapted from Witter et al., 2025)*



**Note.** Adapted (with changes made) from “*A political economy framework for analysing the governance of AI in healthcare in Africa*” by S. Witter, J. Namakula, P. Waiswa, F. Ssengooba, & J. Nabyonga-Orem, 2025, *Globalization and Health*, 21, Article 29. <https://doi.org/10.1186/s12992-025-01129-0>.

This framework treats who participates, under what conditions, and how issues are framed as impacting a policy’s final form. First, the Actors section will help map relevant stakeholders in Kenya’s AI ecosystem. Second, the Context section will explore enabling conditions or constraints such as existing infrastructure capacity or regulatory regimes. Finally, the Framing section will examine if and how health and normative/ethical principles are framed.

### 4.3 Limitations

Before going further, it is worth acknowledging the limitations of this approach. Firstly, by focusing on “the state” as the primary policy organization, the analysis gives more weight to formal government action and may underestimate the influence of other non-state actors (like multinationals or advocacy groups). Secondly, the chosen method of analysis relies on the published version of the policy, meaning internal debates, dissenting views, or any compromises that shaped the policy’s final form cannot be accounted for. Lastly, analyzing a single case study (Kenya) limits the generalizability of any findings.

### 4.4 Actors

#### *Who Was Involved?*

Kenya’s AI policy process has been shaped by a wide set of actors spanning government, academia, industry, civil society, county innovation hubs, development partners, and global

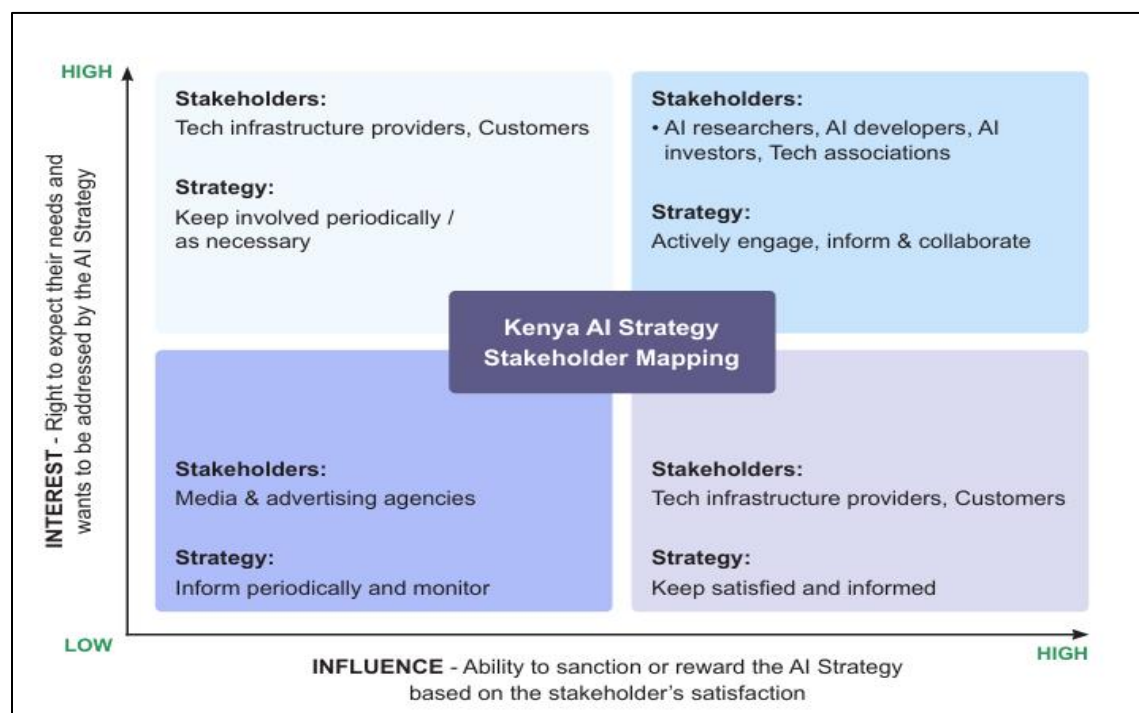
technology firms. The National AI Strategy employed an extensive methodology involving (Kenya Ministry of ICT, 2025, pp. 22-23):

- Key Informant Interviews (KIIs) with government representatives, regulatory agencies, implementation and development partners;
- Focus Group Discussions (FGDs) with stakeholders from industry, academia, and civil society;
- Expert consultations with AI leaders;
- Town-hall sessions held in county innovation hubs;
- A national public online survey through which citizens and organisations could contribute perspectives; and
- Three national stakeholder workshops.

Kenya's strategy is unusual in that it includes an explicit Stakeholder Mapping Matrix analyzing which actors the government thinks have high influence and which have high interest in AI governance (Kenya Ministry of ICT, 2025, pp. 49–52):

**Figure 3**

*Stakeholder influence–interest mapping from the Kenya national ai strategy*



**Note.** From *Kenya National Artificial Intelligence Strategy 2025–2030* (p. 52; Figure 3.1), by Kenya Ministry of Information, Communications and the Digital Economy, 2025, Government of Kenya. <https://ict.go.ke/sites/default/files/2025-03/Kenya%20AI%20Strategy%202025%20-%202030.pdf>

Actors such as AI researchers, AI developers, AI investors, and tech associations are categorised as requiring “active engagement, continuous collaboration, and sustained communication.” Whereas tech infrastructure providers and customers appear lower priority in terms of active engagement with mentions like “keep involved periodically as necessary” and “keep satisfied and informed.”

This mapping is analytically though-provoking because it reflects the government’s assumptions about who drives AI innovation and who is the “recipient” of policy decisions.

### ***The Role of Non-State Actors***

The policy’s “Annex on Collaborators and Partners” (pp. 85-86) includes mentions of several private sector commercial actors who were involved in the policy formulation process, and one of them is Safaricom. This is notable as in the research read for this paper, several authors raised concerns about Safaricom’s market dominance and its influence over digital lending ecosystems in Kenya (Birhane, 2020; Gaffley et al., 2022). Safaricom is the country’s dominant telecommunications and digital-finance company and its infrastructure underpins a large share of Kenya’s AI-enabled fintech and mobile-health tools. The research noted that Safaricom’s systems have been linked to borrower vulnerability due to limited competition and power asymmetries in data-driven financial decision-making (Gaffley et al., 2022).

As Birhane (2020) argues, the involvement of powerful private-sector players – particularly those that are partly foreign-owned – raises important governance questions about whose interests are prioritized in AI policymaking. In the context of AI in healthcare these questions matter a lot. An actor like Safaricom’s presence at the policymaking table may boost innovation, but it also risks steering policy towards commercial interests, like data extraction, if the state is not careful.

## **4.5 Context**

### ***What Did the Literature Say About Enabling Conditions?***

Kenya’s National AI Strategy was formed in a *comparatively* favourable enabling environment. Economically and technologically, Kenya is often described as the “Silicon Savannah” of the central and eastern African region (Diallo et al., 2025; Kwanya, 2023). It has some of the best internet connectivity in Africa, a flourishing fintech and start-up ecosystem, high mobile-phone penetration, and globally recognized digital innovations such as M-Pesa (Kwanya, 2023; Ade-Ibijola & Okonkwo, 2023). It also ranks among the top African performers in government AI readiness indices and digital-skills surveys (Diallo et al., 2025; Okolo et al., 2023). In terms of health, Kenya has a rather developed regulatory and digital-health framework (Townsend et al., 2023). It was the only country in Townsend et al.’s (2023) study of the regulatory landscape of 12 African countries<sup>2</sup> with a standalone e-Health Bill. It has professional

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<sup>2</sup> The 12 African countries are: Botswana, Cameroon, The Gambia, Ghana, Kenya, Malawi, Nigeria, Rwanda, South Africa, Tanzania, Uganda, and Zimbabwe.



guidelines on telemedicine, e-prescriptions and electronic consent, and it also enacted an early Data Protection Act (2019) with a “privacy-by-design” clause (Gikunda & Kute, 2023). All these factors provide a *comparatively* favourable enabling environment for AI R&D.

### ***What Does the Policy Itself Say About Enabling Conditions?***

While the literature had several positives about Kenya’s enabling conditions, it also had mentions of ways in which these could be improved. What was interesting and unexpected was that the state itself acknowledged many of these shortcomings quite comprehensively in its national strategy. The strategy acknowledges that “[its] existing regulatory and legal frameworks to address the unique challenges AI technologies pose are inadequate” (Kenya Ministry of ICT, 2025, p. 20). The policy also explicitly recognizes “Talent Development, Governance, Investments, and Ethics, Equity and Inclusion” as its key enablers in meeting the vision of regional leader in AI R&D (Kenya Ministry of ICT, 2025, p. 84).

The strategy noted how in its consultation processes with KIIs, such things as lack of quality and digitized data, infrastructural gaps, and limited data-sharing mechanisms emerged as key barriers to AI R&D (Kenya Ministry of ICT, 2025, p. 45). They also warned of public mistrust, driven by concerns about unethical AI use, data privacy, misinformation, and bias (Kenya Ministry of ICT, 2025, pp. 45–46). Interestingly, the KIIs also noted power imbalances where big tech firms wield disproportionate influence, while many Kenyan workers remain trapped in entry-level data annotation roles (Kenya Ministry of ICT, 2025, p. 46). Town hall meetings echoed similar concerns – citizens across counties expressed enthusiasm for AI but at the same time, worried about the displacement of workers in labour-intensive sectors (Kenya Ministry of ICT, 2025, p. 47). Participants also emphasised the need for affordable smartphone access and expanded connectivity for AI development (Kenya Ministry of ICT, 2025, p. 48). Overall, it was compelling to see the state openly acknowledge and highlight these concerns in such a transparent manner throughout the strategy.

## **4.6 Framing**

### ***Is health mentioned and how is it framed?***

Within the strategy, “healthcare” is mentioned 22 times and “health” is mentioned 8 times (based on a simple “control+f” search). Healthcare is explicitly listed as one of several “priority sectors” for AI alongside other sectors like agriculture, education, financial services, and public administration (Kenya Ministry of ICT, 2025, p. 7). Throughout the document, health is clearly named but not treated as a stand-alone pillar; instead it appears in a broader economic transformation narrative. It is worth noting that this does not mean that healthcare is “absent” or “not a priority for AI.” If anything, Kenya has some of the highest level of experimentation happening in terms of AI research, development and deployment. For example, AI-assisted TB screening (Zenseye), smartphone-based cervical-cancer screening, and telemedicine and mobile health platforms were being piloted in the country even before this year’s release of the AI strategy (Balogun et al., 2023; Oladipo et al., 2024; Onyango & Ondiek, 2025). This supports

this paper's thesis that having a favourable enabling environment is crucial for responsible AI R&D.

***What normative/ethical principles does the strategy want to advance?***

Normatively, the Kenyan National AI Strategy conveys the following principles guiding it (Kenya Ministry of ICT, 2025, pp. 18–19):

1. Inclusivity and non-discrimination;
2. Participation and co-creation;
3. Transparency and accountability;
4. Ethical and responsible AI, cultural preservation and contextualisation;
5. Environmental sustainability;
6. Economic self-sufficiency; and
7. A local-first approach.

Across the strategy, several passages mention these commitments. For example, the strategy emphasises the need to “protect against negative impacts of externally developed AI solutions” (Kenya Ministry of ICT, 2025, p. 21). It also notes that building local capabilities is essential to ensure that AI systems “are rooted in Kenyan values and contexts” rather than “imported systems that may may not align with the country's unique needs and challenges” (Kenya Ministry of ICT, 2025, p. 21). Public engagement, awareness, and trust-building are described as essential prerequisites for legitimate and responsible AI development (p. 47). Findings from the townhall dialogues also note that participants raised that AI systems must align with “Kenyan cultural norms and values” (Kenya Ministry of ICT, 2025, p. 47)

Despite this, the strategy largely frames its guiding principles using universal AI-ethics language. Overall, while the strategy acknowledges Kenyan cultural norms and values, it stops short of actually saying what these might be. This aligns with critiques in the literature that AI strategies in Africa may be reproducing “imported normative frames” rather than drawing on African philosophical perspectives (Birhane, 2020; Eke et al., 2023; Jobin et al., 2019).

**Conclusion**

Overall, this section shows that Kenya's policy response reflects both the promise and the complexity of governing AI in African contexts. The state is actively trying to strengthen its enabling conditions while navigating diverse actors and competing interests. This makes Kenya a useful case for examining how some African governments are responding to the challenges identified in this paper.

## **Section 5: Conclusion**

This paper set out to answer the question: “How do challenges around enabling conditions prevent a conducive environment for AI and health research and development (R&D)

in Africa?” Across the three thematic sections, the analysis demonstrated that constraints in digital and physical infrastructure, regulatory capacity, funding, and technical skills shape the feasibility of advancing health-related AI. In fact, these gaps can interact with deeper contextual factors like historical mistrust, experiences of algorithmic discrimination, and the lack of alignment with “imported” ethical frameworks to ultimately influence whether AI systems are viewed as legitimate or culturally appropriate. The case study section applied this to the case of Kenya to show how a state must navigate precisely these barriers while keeping in mind issues of trust and contextual relevance. In conclusion, the findings support this paper’s thesis that creating a genuinely conducive environment for health AI R&D in Africa requires not only overcoming larger systemic barriers, but also grounding AI governance in African value systems.

**Final Word Count (excluding on-text citations): ~5,300 words**

## **AI-Use Disclosure**

AI was used in the preparation of this paper in the following ways:

### **ChatGPT 5.1**

- Used ChatGPT to group readings into thematic categories, summarize them for easier review, and flag duplicate articles.
- Used ChatGPT to improve clarity, coherence, and grammar in several sections, and to suggest where the paper could be shortened by removing duplication.
- Used ChatGPT to extract in-text citations, generate APA reference entries, and identify missing bibliographic information, with all citations cross-checked manually.
- Used ChatGPT to draft the list of acronyms and figure captions.
- Used ChatGPT to provide an estimated word-count of paper without in-text citations.

### **Google Gemini (3.0 Pro)**

- Gemini was used specifically to provide a clear, concise definition of “enabling conditions,” which was then cited in the paper as part of the key definitions section.

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### Appendix – Breakdown of Search Strategy Terms

Search Term	Date of Search	Database Used	Total Articles	Reviewed Articles
<b>Agenda Setting in Global Health And AI</b>	Sept. 30, 2025	Google Scholar	975,000	9
	Sept. 30, 2025	Biomed Central	397	5
	Sept. 30, 2025	PubMed	35	1
	Sept. 30, 2025	Scopus	5	1
	Sept. 30, 2025	Science Direct	5,872	1

Search Term	Date of Search	Database Used	Total Articles	Reviewed Articles
<b>AI + Healthcare + Agenda</b>	Oct. 4, 2025	Google Scholar	535,000	5
	Oct. 4, 2025	Biomed Central	413	Same articles as above search term for the most part.
	Oct. 4, 2025	PubMed	144	1
	Oct. 4, 2025	Scopus	123	0
	Oct. 4, 2025	Science Direct	4,975	5

Search Term	Date of Search	Database Used	Total Articles	Reviewed Articles
<b>National AI Strategies Africa</b>	Nov. 22, 2025	Google Scholar	2,580,00	20
	Nov. 22, 2025	Biomed Central	1,320	1
	Nov. 22, 2025	PubMed	1,179	0
	Nov. 22, 2025	Scopus	44	6
	Nov. 22, 2025	Science Direct	21,874	1

Search Term	Date of Search	Database Used	Total Articles	Reviewed Articles
<b>Artificial Intelligence + Healthcare + Framing</b>	Nov. 22, 2025	Google Scholar	146,000	4
	Nov. 22, 2025	Biomed Central	1,097	4
	Nov. 22, 2025	PubMed	280	1
	Nov. 22, 2025	Scopus	67	0
	Nov. 22, 2025	Science Direct	14,552	4

Search Term	Date of Search	Database Used	Total Articles	Reviewed Articles
<b>Artificial Intelligence Policy Making</b>	Nov. 22, 2025	Google Scholar	5,350,000	2
	Nov. 22, 2025	Biomed Central	3,370	1
	Nov. 22, 2025	PubMed	1,275	4
	Nov. 22, 2025	Scopus	2,000	0
	Nov. 22, 2025	Science Direct	89,413	3