Challenges and Prospects of Deploying AI and Machine Learning for Clinical Diagnosis in African Healthcare

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Abstract

The integration of artificial intelligence (AI), machine learning (ML), and robotics into clinical diagnosis has become prevalent. For example, ML-driven image recognition has demonstrated remarkable efficacy, prompting clinicians to rely increasingly on these technologies for "accurate" medical diagnoses and prognoses of diseases. Although these advancements have exhibited their relevance and effectiveness in medically advanced regions of the Global North and selected areas in the Global South, the question arises as to their viability within the healthcare landscape of Africa, given contextual variations. In this paper, I delve into the potential efficiency of deploying these technologies within African healthcare, aiming to address these contextual concerns. Employing a phenomenological methodology, I demonstrate that the deployment of these technologies might inadvertently introduce biases and discrimination against Africans. This stems from the inherent nature of the data used to develop these technologies, primarily sourced from healthcare experiences in designing nations, coupled with the pervasive algorithmic biases prevalent in contemporary ML systems. I call for a paradigm shift in AI and ML development. I propose that African nations should proactively engage in the design of healthcare AI and ML technologies that are attuned to distinct African conditions, prevalent medical conditions, and prognostic methodologies. Key prerequisites include the establishment of robust infrastructure for efficient data collection and storage of electronic healthcare records and capturing the intricacies of day-to-day healthcare encounters across the African continent. Furthermore, I underscore the importance of contextual sensitivity in applying AI and ML within African healthcare.

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Introduction

What are the ethics of designing context-sensitive AI and medical ML technologies within Sub-Saharan African healthcare? Are current ML technologies trustworthy, and can they effectively carry out complex medical diagnoses in Sub-Saharan Africa? In this paper, I argue that to design effective, trustworthy and ethical ML for Africa, these designs ought to centre on African agency, that is, attuned to the African experiences, values, and healthcare norms, on the one hand. On the other hand, a context-sensitive design of medical MLs in Sub-Saharan Africa will be a technology that understands the factual and value-laden judgement on what is considered as health and diseases in the region. Furthermore, it is imperative that medical AI and ML technologies are designed using healthcare datasets from Sub-Saharan African healthcare systems rather than externally sourced from elsewhere. My claim that healthcare datasets must be sourced within Sub-Saharan Africa should not be understood as a homogenous data-gathering process, leading to a generic design of medical AI and ML technologies. If this is done, it defeats the aim of this paper, as a homogenous/generic design of medical AI and ML for Africans implies that Africans have the same healthcare values and norms captured in their datasets. I engage with this point later on in this paper.

My above-prized approach is necessary for designing ethical, trustworthy, and value-sensitive AI and medical ML technologies in Sub-Saharan Africa because of the disruptive nature (which I will clearly explain later) of these technologies. AI encompasses “a broad set of sophisticated computer-based statistical tools” (Ranka et al. 2021:26) and may be defined as “an area of computer science devoted to developing systems that can be taught or learn to make decisions and predictions within specific contexts” (Smith and Neupane 2018:10). AI systems “display intelligent behaviour by analysing their environment and taking actions — with some degree of autonomy — to achieve specific goals” (EC 2018: n.p.). AI algorithms are particularly useful because they “can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments” (OECD 2019b:7).

Given the capacity of AI, the technology has become prevalent in healthcare and/or medical decision-making. It is worth noting that the application of AI in healthcare is not a recent innovation. Early uses occurred in the 1970s when early forms of AI were used to diagnose and treat pathologies such as glaucoma and other infectious diseases by implementing Bayesian approaches (Owoyemi et al. 2020). However, with the growing application of ML techniques, a subfield of AI, in the second decade of the present century, AI has become more significant in medicine and, increasingly, in public health. Image recognition, in particular, has become highly effective, and clinicians increasingly rely on ML technologies for clinical diagnosis and prognosis of medical conditions (Grote and Berens 2019).

While the use of ML techniques has been applied to the diagnosis of neurodegenerating diseases such as Parkinson’s, Alzheimer’s, mild cognitive impairment (Myszczynska et al. 2020), cardiovascular diseases (Ranka et al. 2021), or skin diseases such as skin cancers (Esteva et al. 2017), to mention a few, the technology generally suffers from algorithmic bias, misrecognition, and discrimination against specific demographics of the human population, especially along racial lines. ML algorithmic bias is a result of the technology's poor track record in recognising people of certain populations, such as Asians and those categorised as Black Africans (Angwin et al. 2016; Aquino 2017; Barocas and Selbst 2016; Buolamwini and Gebru 2018; Castro et al. 2023; Forrest 2021; Greene 2023; Hellman 2020; Holm 2023; McCullom 2017; Sloane 2022).

The problems mentioned above stem from the misrepresentation and/or poor representation of the aforementioned population in the ML designing dataset. In healthcare, the problem of misrepresentation and/or poor representation of some populations in ML designing datasets stems from healthcare/medical decision-making and distribution of healthcare/medical resources due to socioeconomic inequalities (Braveman et al. 2010; Cavallero 2019; Ekmekci and Arda 2015; Marmot et al. 1991; Wilkinson 1996; Wilkinson 2003). However, in this paper, focusing on the African AI ecosystem, I claim that most ML technologies are not developed within the African continent; hence, the less inclusivity of data that captures African daily lived experiences in the designing dataset of AIs and MLs results in algorithmic bias and discrimination against Africans.

To solve the problem of algorithmic bias and discrimination in AI and ML technologies in healthcare, I make the following new Submissions. First, the technologies should be designed in Africa and encoded with the necessary features to understand the African experiences. Second, the majority of the designing datasets for these technologies must be sourced from African healthcare systems, as this is necessary for the efficient design of medical AI and ML technologies for African healthcare that are trustworthy. Third, the African Union must make pragmatic efforts to ensure that the primary data collection techniques and storage systems are provided in healthcare systems across the continent for efficient data collection and storage for the research and design of ethically efficient and trustworthy AI and ML technologies. Finally, to achieve value-sensitivity in the design of medical AI and ML for healthcare in Africa, the designing ethical guidelines and frameworks must be centred around dominant African values, cultures, and norms.

This chapter has three sections. In the first section, I outline the promises of AI and ML technologies

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in healthcare. Furthermore, I expose some of the implications and challenges of ML techniques in healthcare. In the second section, I engage with the technological landscape and ecosystem in Africa. The aim here is to see Africa's readiness to engage with the designs of medical AIs and MLs. Additionally, I show the necessity for an African design of AI and ML for Africans. Finally, I make some novel pragmatic recommendations for a way forward on how Sub-Saharan Africa can advance and upskill its technology research and design, especially within the healthcare domain.

The Promises of Artificial Intelligence and Machine Learning Technologies

The development, deployment, and application of AI in different industries are increasing rapidly (Borenstein and Howard 2021). With this rapid increase, AI is now occupying a transformative space in our societies as it continues to affect lives, experiences, and the social, political, and economic landscapes (Luan et al. 2020). To understand what AI means, many theorists have theorised this technology in different ways while bearing in mind the positive and adverse effects of the technology (EC 2018; Smith and Neupane 2018; Tremblay 2017; Ugar 2022; Van de Poel 2020).

The definition of AI has progressed or has been conceptualised according to the different social milieu and the effects of AI within each milieu. For instance, between the 1950s to 1980s, AI was understood solely to be a branch of science responsible for developing intelligent systems (Brey and Soraker 2009; Hayes and Ford 1995; Luxton 2016). This conception of AI stems from Alan Turin's (1950) exposition of AI in Turin's famous argument, "Can machines think?" Since Turin introduced the notion of AI, other definitions of AI technology have sufficed. AI is sometimes conceptualised as a technology designed to perform activities requiring intelligence (Flowers 2019). In the last two decades, the definition of AI has transcended beyond the mere conceptualisation of the technology as just a machine. AI is now conceived as a technology meant to mimic the intricacies of human interactions, comprehension, sensing, actions, and intelligence (Hamet and Tremblay 2017; Smith and Shum 2018). Given these qualities of AI, it is said to change different aspects of our society, such as how we do business, public health, foster innovations, increased productivity and service delivery, and agriculture (Borenstein and Howard 2021).

In the current social milieu, the definition that best captures the current role AI plays in society and how the technology is viewed is provided by the theorist Ibo van de Poel (2020). Van de Poel defines AI as a sociotechnical system made of "technical hardware, human behaviours, and social institution" (2020:391). For AI to function properly, the system relies on certain portfolios or Subfields, such as machine and deep learning, natural language processing, and computer vision (Esteva et al. 2019). ML, a Subfield of AI, enables the sociotechnical system to learn from the pool of data that has been made available to the system to allow it to make predictions and decisions for users (Norgeot et al. 2019; Ranka et al. 2021). Additionally, deep learning, as a Subfield of machine learning technology, using large datasets has enabled ML algorithms to interact with data and other aspects of machine learning systems such as image recognition, language and speech recognition and processing to carry out tasks (Esteva et al. 2019; LeCun et al. 2015). These AI tools are essential in public health and medicine to carry out diagnosis, as I will show in the preceding paragraphs.

ML technology has become an important aspect of public health and medicine, especially for diagnosing and treating diseases. This technology has the potential to transform healthcare. Given the potential of ML, there has been a recent interest to further introduce the technology in medical and healthcare decision-making (Esteva et al. 2019; Grote and Berens 2019; Myszczynska et al. 2020). This is on the basis that the techniques have demonstrated expertise and accuracy in diagnosing diseases such as neurodegenerating diseases, skin lesions, skin cancer, and fundus images (Esteva et al. 2017; Grote and Behrens 2019; Topol 2019). With the accuracy of machine learning algorithms in clinical diagnosis and expertise in predictive abilities, clinicians will benefit immensely from the assistance the technology will provide them in assessing patients' risks individually on complex datasets.

Machine learning technologies are expected to move from curing diseases to preventing diseases in the near future (Myszczynska et al. 2020). For example, a significant number of the global population is ageing, and the risk of neurodegenerating diseases is increasing. Age is a significant explanans of neurodegenerative diseases like Parkinson's, Alzheimer's, mild cognitive impairment, and motor neuron diseases. With the high cost of treating these diseases, the call for using ML technology for early clinical diagnosis and prognosis is imperative.

While machine learning technologies have great promises in public health and/or medicine, there are some significant ethical concerns that these technologies raise. One is the issue of algorithmic bias, misrecognition, and discrimination due to an imbalance in datasets used to train AI algorithms (Angwin et al. 2016; Buolamwini and Gebru 2018; Castro et al. 2023; Forrest 2021; Greene 2023; Hellman 2020; Holm 2023; McCullom 2017).

For example, evidence shows that facial recognition (FRT) and recidivism software have higher accuracy among Caucasians than African Americans, Africans, and Asians (Buolamwini and Gebru 2018; McCullom 2017). In some instances, FRT has lower accuracy for darker skin colours than lighter skin (Buolamwini and Gebru 2018). This raises a severe problem for clinical diagnosis of people of colour, such as African Americans, Africans, and Asian people, given the current biases and the low accuracy of the representation of these populations in machine learning software. This problem may seem like a practical problem. However, I argue that bias in machine learning technologies results from conceptual, methodological, and ethical issues that require some philosophical skills to resolve.

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For example, with the current designs of machine learning algorithms, there is a challenge that people of 'minority identities', such as race (blacks, Asians and others), may find it challenging to access proper healthcare services due to the poor representation of these populations in datasets used in designing these technologies. However, issues of poor representation of 'minority populations' in datasets result from the basic structures of societies and the unfair distribution of societal goods across different demographics in society (Ugar 2023). Issues of these kinds have not been sufficiently dealt with due to the shortcomings of the current guiding principles for the distribution of social goods in society. However, I will leave the above problem for another project. In this paper, I narrow my concern to the impact of structural biases and discrimination in algorithms within the context of Sub-Saharan Africa. I contend that it is a prerequisite for Africans to begin producing their medical machine learning technologies to circumvent the abovementioned problems of machine learning technologies. This is because ML technologies, especially those in healthcare, are designed using healthcare datasets from the context where they are designed to achieve efficiency. If these technologies are not currently designed here in Sub-Saharan Africa, it means the datasets, which capture the worldviews of Sub-Saharan Africans are not present in the design to create efficiency.

However, the pragmatic question to ask is: Can Sub-Saharan Africans design their medical technologies? Since the data used in designing medical technologies are produced from medical and/or healthcare judgments, such as treatment judgments of clinicians over a period of time, I ask whether Sub-Saharan African healthcare systems have the requisite technologies needed for the extraction of healthcare data for research and designs of medical technology. My answer is not in the affirmative. However, Africans producing their technology is the best alternative to mitigate structural biases and discriminations in algorithms used in the continent to tackle healthcare challenges.

It is imperative for Africans to resist the proclivity to deploy technologies elsewhere to deal with their healthcare challenges. According to my intuition, technologies designed elsewhere are not produced with African agency in mind, such as values, ethics, lived experiences, and worldviews, given that the data used in designing these systems do not dominantly come from Africa. Furthermore, given the problem of structural biases and discrimination that people of colour and black people have experienced, deployed technologies are less trustworthy. As a result, this paper calls for the design of medical technologies within Africa which considers the contextual healthcare experiences of Africans. For the above to be realistic, Africans must look inward towards their indigenous knowledge systems, values, and lived experiences to enable them to design context-sensitive machine learning technologies for their healthcare systems. Designing these technologies in Africa can be made possible by capturing data from Africa that emanates from the continent, as well as capturing their lived experiences, especially within the healthcare domain.

However, while the above is ideal, I am not oblivious to some of the contextual challenges that may impede an African design of medical machine learning technologies. As a result, in the next section, I show some challenges Africans might face in designing their healthcare machine learning technologies. However, I also provide motivations and rationale for dealing with these challenges to create a sustainable and efficient technological ecosystem in Africa that can see to the design of efficient ML technologies.

Technological Landscape and Ecosystem in Africa

There have been several conversations regarding the design of AI in Africa, which has been championed by the African Union (AU). The goal of the AU has been intended to protect African interests from disruptive technologies as well as ensure that the continent is prepared to welcome this technological revolution, construed broadly as the Fourth Industrial Revolution (4IR), which comprises the Internet of Things (IoT), robotics, AI, genetic engineering, and others. The AU has ensured that from the regulatory side of this discourse, Africans are protected. The AU has also ensured that there is a template which could enable Africans to take advantage of this technological revolution.

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For instance, the AU's panel, the African Union High-Level Panel on Emerging Technologies, which was instituted in 2016 consisting of expert groups, was set to ensure that it provides expert guidance to the AU on matters of technology and how to harness these emerging technologies for the benefits of Africans (AUDA-NEPAD 2016). Given that the AU is very interested in the responsible use of social technologies, the expert group is designed to ensure Africa's readiness to engage with emerging technologies. Furthermore, the AU also instituted the African Union Working Group to oversee the development of AI in 2019 (African Union 2019). The working group's focus is to ensure there is development and acquisition of technical skills, efficient data infrastructure growth across member states, and support for interstate research on AI (Ministry of Communication and Information Technology 2019). Other groups like the African Commission on Human and People's Rights (ACHPR) are also tasked to undertake multidisciplinary studies to grasp how AI impacts the continent. The group is also ensuring that it develops effective frameworks that will ensure effective AI governance and encourage the responsible use of AI in the continent (ACHPR 2021).

Before I go further, it is important that I clarify my use of the term 'Africa' or 'Sub-Saharan Africa' to encompass all the countries in this region. My use of the term 'Africa' as a group should not be understood as blindly labelling the narrative of the entire continent from a monolithic lens, as this is a common practice. One of the unconscious things that is usually done in the discourse on AI, especially in the narratives of the technology ecosystem in Africa, is the assignment of geographical labelling, which is problematic. Geographical labelling here is the assumption that people are the same or monolithic in a particular geographical area. For instance, Africa is mostly considered monolithic in anthropological scholarship, and researchers from this domain tend to conceive Africans with the "myth of unanimity" (Segun 2014).

The "myth of unanimity," in simple terms, is conceived as the erroneous notion that individuals within or from a certain region tend to think alike, and their beliefs and perceptions of reality are intertwined (Segun 2014). This sort of thinking ascribes homogeneity to Africans by circumventing the reality that the continent has 54 political states with inhabitants with different features, cultures, and ethical values and ethos. In this sense, when the myth of unanimity is carried out, people within that context, in this case, Africans, are stripped of their individuality and collective belief is assigned to them (Hountondji 1983:60). An example of the myth of unanimity here is to conceive Africans as having a homogenous approach to healthcare, a value-laden judgment of diseases, and approach to mitigating health challenges. However, the assumptions above are not always accurate but merely an uncritical form of geographical labelling.

However, exposing what geographical labelling means allows me to use the label 'Africa' or 'Sub-Saharan Africa' without falling into the myth of unanimity. I use geographical labelling similarly to how Thaddeus Metz (2015) uses the term. Here, Metz conceives geographical labelling as the method of picking out salient features that are recurrent within a particular geography and not in other geographical regions. As Metz claims, such a method should not be considered a form of essentialising these features. By essentialising, I mean creating an impression that the features of a particular geography are not found elsewhere. Geographical labelling only deals with recurrent features (Metz 2015:1176; Segun 2020). A recurrent feature is a feature that is dominant within a particular environment. For example, one can say that Kangaroos are more prevalent in Australia than anywhere else. This claim does not imply that there are no Kangaroos in other parts of the world; instead, it means that there are more Kangaroos in Australia than in other parts of the world. Another example, patterning to the AI ecosystem, could be that there are more AI industries in China, the US, and India than in Africa. Again, the claim is not that Africa does not have AI infrastructures but that the presence of these infrastructures is not dominant in Africa compared to the abovementioned countries.

My use of geographical labelling ought to be understood strictly along the above lines, highlighting those dominant features in a particular domain rather than assigning a collectivist notion of those places. Africa has salient features unique to the continent due to some socioeconomic and historical features that countries within this political region share. As a result, it is in line with these thoughts that I use Africa/Sub-Saharan Africa as a reference in making my case for the design of medical AI infrastructure in Africa. Furthermore, I think that Africans, mainly Sub-Saharan Africans, share a similar approach to remedial medicine. There are similarities between Africans addressing health challenges through traditional medicine like herbs, roots and others. Additionally, Africans share similar challenges in healthcare across the different countries within the continents, that is, challenging infrastructures, access to vaccines, and other socioeconomic and political factors. These factors justify my usage of the label 'Africa' or 'Sub-Saharan Africa' to make my case.

On the above account, it is worth mentioning that Africa is getting in line with the design of AI and setting infrastructures in place for an efficient and effective AI ecosystem within the continent. This narrative is vital to point out, given the depiction of Africa by the media to the rest of the world as a region that is incapacitated to develop itself. Furthermore, I seek to make a case that Africans can develop their technologies, especially medical machine learning technologies, that mirror African lived experiences given the number of emerging experts within the continent.

Why is it very necessary for Africans to develop technologies that mirror African lived experiences? There are several reasons, that form the yardstick for my proposition that Africans should develop their medical machine learning technologies, some of which I have clearly espoused (structural discriminations and biases) in the previous section. A further reason is based on the view that

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technologies are not innocuous; when adopted, they influence users' behaviours in many ways (Ihde 1993; Rajagopal 2014; Ugar 2023b). This includes changing how the users begin to lead their lives, visualise the world, and engage with one another while carrying out their day-to-day tasks/businesses. Furthermore, as espoused in the previous section of this paper, current machine learning technologies are guilty of structural biases and discriminations, given their designing datasets. However, in the following paragraphs, I would like to stick to the value influences technologies have on their users to make a case for the need for value-sensitive design (which can only stem from Africa for Africa) of medical technologies that emerge from Africa.

New emerging technologies influence their users more because of their social nature. It is the reason why many researchers have termed emerging technologies as "sociotechnical artefacts" (Ananny 2016; Reider et al. 2021; Van de Poel 2020). For example, Ibo van de Poel (2020) contends that sociotechnical artefacts like AI and machine learning are designed to comply with specific values, mostly the values of their designers. These designers integrate their institutional values into these systems in order to ensure that the values of the social institutions align with the values of the systems they design. As a result, these technologies are not value-neutral but value-laden instruments, such that when they are transferred from one locale into another, they come with the values of their designers (Ugar 2023b). This view has been expatiated by Don Ihde. Ihde argues that technology transfer has to do with the "introduction of some set of material artefacts out of their original context of human praxes or techniques, into some other cultural context" (1993:32). When technology transfer occurs, value transfer also takes place, leading to the disruption of the values of the receivers of this technology. As a result, given their social nature, medical AI technologies tend to be disruptive. This conception of disruption is similar to Hopster's (2021) conception of the term. Here, Hopster conceives social disruptive technologies as those that tend to disrupt our values, current traditional norms, and how we perceive the world through their unpredictability (2021:2-3; Ugar 2023a).

Given that technology, like AI or machine learning, is designed based on their designers' institutional values and norms, it is crucial to understand the contextual influences of their designers on the sociotechnical artefacts. It is prima facie that values and norms are not universally construed, given that each society has some important values and norms that shape them; what is essential to one society might not be important to another. This is precisely why Africans ought to be at the centre of their design and coding important values into their technologies for clinical diagnosis. Furthermore, as I have argued elsewhere (Ugar 2023b), the transfer of technologies from elsewhere may lead to what I conceived as technological colonialism, a kind of colonialism which is common in our current digital milieu. Additionally, designing our technologies within Africa will make the technology more trustworthy. When users in Africa know that their technologies are designed in Africa, they may have moral, emotive, and psychological motivations to trust the technologies. This is because they may feel that the designers understand their needs, cultures, lived experiences, values, and morals and have encoded these in the systems. Furthermore, because of current structural biases and discrimination and past histories of colonialism and neo-colonialism, AI and machine learning designs from Africa will be more trustworthy by Africans than technologies that are deployed elsewhere. I will not go further into this discussion, as the discourse on trustworthiness in AI and colonial history is broad and cannot be fully captured here. However, moving forward, I will show some of the developments in AI within Africa in the last decade.

Some African countries are ensuring that they foster regulatory and economic readiness for AI design and usage. These countries are proactive in implementing regulations to meet the desire to leverage the prospects of AI for economic development in their countries. Some countries within the African continent are putting in place the infrastructures and other strategies like education. However, even though these countries have been proactive in ensuring the above, the African region still ranks very poorly in the AI government readiness index, scoring on average at around 31.61 (Nettel et al. 2021:44). An explanans of these could be based on the poor performance given the continent's poor data infrastructure, an

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essential requirement for efficient AI ecosystem. I will return to this point shortly, as it is part of the basis for my argument in this chapter.

According to a Government AI Readiness Index (2021) created by Oxford Insights, Mauritius, ranking 58th out of 160 countries, is leading Africa's government AI readiness index. Other countries like Egypt (65th), South Africa (68th), Seychelles (70th), and Kenya (78th) are also making progress (Shearer et al. 2020). We can learn from these rankings that most African countries are still not ready compared to countries in South Asia, Europe, and America, which have successfully implemented a national strategy for AI. The hope is that the AU Working Group on AI can develop a consistent template to ensure that the strategy for AI cuts across all African countries while considering their contextual needs and differences (Gilbert 2020).

Despite not ranking in the top 50 countries in terms of the Government AI Readiness Index in the 2020 report – which groups countries based on the measures they have put into place like infrastructures – "African countries are relatively prepared in the Data and Infrastructure pillar, followed by the Government pillar and then the Technology Sector pillar" (Shearer et al. 2020). One could see some positive lights in this regard. However, the growth in the AI ecosystem in Africa results from some knock-on effects of technological globalisation in Africa on account.

The notion of technological globalisation here implies the distribution of technologies globally, but mostly from the Global North to the South. This aspect of the AI narrative boils down to the point I have made earlier and on which my argument is centred. In the sense that technological globalisation, as construed above, has shaped the African technological ecosystem in different directions. The private sector has spearheaded this sector. It has formed the substructure upon which African countries have experienced the rapid growth of technology based on the advancement of telecommunication networks like the Internet. Undoubtedly, telecommunication plays an essential role in fostering the development of AI products. With an internet rate of 46.2% in the 1.3 billion people in 2021, a total number of 634,863,323 Africans have access to the internet (Internet World Stats 2021). With a growing young population, of which two-thirds are ages 14-19, Africa has the potential for growing global internet users. As such, there is a growing and rapid investment within the technology sector within the continent.

However, this development has centred largely on technology transfer, which I discussed earlier. For instance, during the uprising of COVID-19, the United Nations Development Programme provided robots to some African countries to assist frontline healthcare workers. These robots were designed by a Belgian robotic company called "Zora Bots," and the deployed robots were given African names. However, the appearances of the robots reflected the appearances of their designers, that is, white bodies with blue eyes (Botha 2021:124). In as much as there are no prima facie problems with such designs, the underlying challenge that I am trying to point out here is that technologies are designed to mirror and replicate the consciousness (values, social norms, and morals) of their designers.

As mentioned earlier, the problem of technology transfer is that most of the work done is less representative of African ethos, values, tenets, worldviews, realities, and modes of perceiving the world. As a result, these technologies are conceived to be an imposition of the institutional values of their emerging locale on the African locale. Furthermore, different designs of AI have shown bias and discrimination towards Africans along the lines of race, which shows the less representation of Africans, their cultures, and values in the design of AI. Given this, some researchers have called this techno-colonialism or digital colonialism and called for the decolonisation of AI (Abeba 2020; Ugar 2023b). However, in this current study, rather than decolonisation, I recommend that Africans get actively involved in the design of AI, especially medical AI and machine learning technologies that capture their lived experiences and perceptions of health and diseases. It is my view that to decolonise is to ask that technologies should account for African realities. However, that is too much to ask, considering that we do not fund these projects. Instead, I prescribe that Africans begin to fund their AI projects to ensure that they have the agency, given their financial role in the design of the technologies, to include features necessary to ensure an effective design of these technologies that capture their realities. To ensure the feasibility of the above, I make the following pragmatic recommendations in the final section of this paper.

Pragmatic Recommendations for the Design of Medical Technologies within Africa

The internal design of medical machine learning technologies within Africa is important for the African AI ecosystem based on the reasons I have mentioned in the previous sections. Nevertheless, most importantly, designs stemming from Africa will give Africans the kind of agency and spike trustworthy use of the technologies. Over a period of time, structural adverse like biases and discrimination in machine learning algorithms may be reduced. However, given the current AI ecosystem in Africa and its reliance on machine learning technologies designed elsewhere, especially those in healthcare, it does not seem feasible that Africans are at the forefront of the technological revolution with the requisite skills and infrastructure to design their technologies. However, with some efficient policies in place, I contend that in the near future, Africans will be capable of designing their medical machine learning technologies and machine learning technologies for other domains. To contribute to setting efficient policies in Africa, I make the following prescriptive recommendations.

Efficient Healthcare Infrastructure for Data Availability: As pointed out earlier, data is the most critical component for designing efficient medical machine learning technologies. Given the complexity of clinical diagnosis, it is imperative that we design medical machine-learning technologies with accurate datasets. The best way we can achieve this in Africa is to strengthen our healthcare system with state-of-the-art techniques to collect healthcare data ranging from consultations to treatments of patients. From my intuition, given my experiences with several healthcare facilities in Nigeria and South Africa, data are still recorded manually in most healthcare facilities across the continent, especially in more prominent public hospitals. Sometimes, these manual files are misplaced or destroyed (unintentionally). Given some of the contingencies of manual collection of data, it is crucial that African governments invest in computerised data collection methods for efficiency and robustness. Furthermore, African governments should ensure that more focus and efforts are channelled into public healthcare services, given that they accommodate most of the population in every country. This can lead to more data production as well as diverse datasets.

Robust Investment in Building Machine Learning Infrastructures on the Continent: As I have shown earlier, the technology infrastructures in Africa are still very poor and less encouraging. The AU should invest more in building efficient infrastructures within the continent. These infrastructures should be funded by the AU or request for partnerships and investments elsewhere, of which the AU should have the power for most of the decision-making on how and what technology and skills are necessary. There are different machine learning initiatives in Africa, like DeepLearningNdaba and others. However, more must be done in this area to equip Africans with the necessary skills. Furthermore, while there have been incentives for Africans to engage in STEM disciplines, there should also be incentives for Africans to pay attention to disciplines that critically engage with the effects and implications of machine learning technologies in societies. The technical and social inquiries of technologies must go concomitantly.

Practical and Robust Data Policy in Africa: The AU should also ensure that it puts in place robust data policies within the continent, similar to the EU data laws and regulations. This will ensure that data generated from Africa are kept in Africa and do not leave the continent. This can be an added advantage for the continent to develop patent and intellectual properties of their unique innovations.

Conclusion

In this paper, I have highlighted some of the significant prospects and challenges of deploying machine learning technologies for clinical diagnosis in Africa. However, I argued that for Africans to have agency and trustworthiness in their medical technologies, the technologies must be designed within the continent using data that captures the healthcare and lived experiences, values, and worldviews of their context. As clearly argued, the above is imperative because of structural biases and discrimination of current algorithms due to poor datasets and how this might be problematic in Africa due to technology transfer. However, as exposed in section two of this chapter, I am not oblivious to the challenges designing technologies for clinical diagnosis in Africa might face. As a result, I made some pragmatic recommendations in the last section of this chapter. The significance of my paper is that it draws from the issues of structural biases in AI to provide practical ways AI can be designed in Africa for clinical diagnosis to strengthen trustworthiness in these technologies. However, the limitation of my paper is that it does not rely 'so much' on making empirical claims but is based broadly on conceptual analysis. I leave the empirical aspect of this study to empirical social scientists to conduct further research on.

References

African Commission on Human and Peoples' Rights. (2021). *Resolution on the need to undertake a Study on human and peoples' rights and artificial intelligence (AI), robotics and other new and emerging technologies in Africa - ACHPR/Res. 473 (EXT.OS/ XXXI) 2021* [Press release]. Available from: https://www.achpr.org/sessions/resolutions?id=504 [accessed on 24/11/24].

African Union. (2019). *African Digital Transformation Strategy and African Union Communication and Advocacy Strategy among major AU initiatives in final declaration of STCCICT3* [Press release]. Available from: https://au.int/en/pressreleases/20191026/african-digital-transformation-strategy-and-african-union-communication-and [accessed on 24/11/24].

Ananny, M. (2016). Toward an ethics of algorithms: Convening, observation, probability, and timeliness. *Science, Technology, & Human Values*, 41(1), pp. 93–117.

Angwin, J., Larson, J., Mattu, S., and Kirchner, L. (2016). Machine bias. *ProPublica.* Available from: https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing [accessed on 24/11/24].

AUDA-NEPAD (2016) *African Union High-Level Panel on Emerging Technologies (APET)*. Available from: https://www.nepad.org/microsite/african-union-high-level-panel-emerging-technologies-apet [accessed on 24/11/24].

Aquino, Y. (2017). Big eye surgery: The ethics of medicalising Asian features. *Theoretical Medicine and Bioethics*, 38(3), pp. 213–225.

Barocas, S. and Selbst, A. (2016). Big data's disparate impact. *California Law Review,* 104(671), pp. 671.

Botha, C. (2021). Gender and humanoid robot: A somaesthetic analysis. *Filosofia Theorectica: Journal of African Philosophy, Culture and Religions,* 10(3), pp. 119-130.

Buolamwimi, J. and Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. *Proceedings of Machine Learning Research*, 81(2018), pp. 1-15.

Braveman, P., Cubbin, C., Egerter, S., Williams, D. and Pamuk, E. (2010). Socioeconomic disparities in health in the United States: What the patterns tell us. *American Journal of Public Health*, 100 Suppl, 1(Suppl1), S186-S196.

Brey, P. and Søraker, H. (2009). Philosophy of computing and information technology. *Philosophy of Technology and Engineering Sciences,* Elsevier, pp. 1341–1407.

Cavallero, E. (2019). Opportunity and responsibility for health. *The Journal of Ethics*, 23(4), pp. 369-386.

Ekmekci, P. and Arda, B. (2016). Enhancing John Rawls's theory of justice to cover health and social determinants of health. *Acta Bioeth*, 21(2), pp. 227-236.

Esteva, A., Kuprel, B., Novoa, R., Ko, J., Swetter, S., Blau, H. and Thrun, S. (2017). Dermatologist-Level classification of skin cancer with deep neural networks. *Nature,* 342(7639), pp. 115–118.

Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., Corrado, G., Thrun, S. & Dean, J. (2019). A guide to deep learning in healthcare. *Nature Medicine*, 25(2019), pp. 24-29.

European Commission. (2018). *Artificial intelligence for Europe*. Available from: https://www.europeansources.info/record/communication-artificial-intelligence-for-Europe/ [accessed on 24/11/24].

Flowers, C. (2019). Strong and weak AI: Deweyan considerations. *AAAI Spring Symposium: Towards Conscious AI Systems.* Available from: https://ceur-ws.org/Vol-2287/paper34.pdf [accessed on 24/11/24].

Forrest, K. (2021). *When machines can be judge, jury, and executioner: Justice in the age of artificial intelligence.* Hackensack, NJ: World Scientific Publishing Co. Pte. Ltd.

Gilbert, P. (2020). Mauritius, Egypt and SA are Africa's most AI ready. *Connecting Africa*. Available from http://www.connectingafrica.com/author.asp?section_id=761&doc_id=765789 [accessed on 24/11/24].

Greene, C. (2023). AI and the social science: Why all variables are not created equal. *Res Publica*, 29(2023), pp. 303-319.

Grote, T. and Berens, P. (2019). On the ethics of algorithm decision-making in healthcare. *Journal of Medical Ethics*, 46(2019), pp. 205-211.

Hamet, P. and Tremblay, J. (2017). Artificial intelligence in medicine. *Metabolism* 69(2017), pp. 36-40.

Hayes, P. and Ford, K. (1995). Turing test considered harmful. *Proceedings of the International Joint Conference on Artificial Intelligence, Monreal*, 1(1995), pp. 972-977.

Hellman, D. (2020). Measuring algorithmic fairness. *Virginia Law Review*, 106(4), pp. 811-866.

Holm, S. (2023). The fairness in algorithm fairness. *Res Publica*, 29 (2023), pp. 265-281.

Hopster, J. (2021). What are socially disruptive technologies? *Technology in Society*, Vol. 67(2021), pp. 1-8.

Hountondji, P. J. (1996). African philosophy: Myth and reality. Bloomington: Indiana University Press.

Ihde, D. (1993). Technology as cultural instrument. In: Ihde, D., ed. *Postphenomenology: Essays in the postmodern context*. Illinois: Northwestern University Press, 207-215.

Internet World Stats (2021). *Africa.* Available from https://www.internetworldstats.com/africa.htm [accessed on 24/11/24].

LeCun, Y., Bengio, Y. & Hinton, G. (2015). Deep learning. *Nature,* 521(2015), pp. 436–444.

Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S.J., Ogata, H., Baltes, J., Guerra, R., Li, P., and Tsai, C.C. (2020). Challenges and future directions of big data and artificial intelligence in education. Frontiers in Psychology, 11(580820), pp. 2748.

Luxton, D. (2016). An introduction to artificial intelligence in behavioural and mental health care. *Artificial Intelligence in Behavioural and Mental Health Care*, ***Elsevier***, pp. 1–26.

Marmot, M., Smith, G., Stansfeld, S., Patel, C., North, F., Head, J., White, I., Brunner, E. and Feeney, A. 1991. Health inequalities among British civil servants: The Whitehall II Study. *Lancet (London, England),* 337(8754), pp. 1387-1393.

McCullom, R. (2017). Facial Recognition Technology is both Biased and Understudied. Available from: https://undark.org/2017/05/17/facial-recognition-technology-biased-understudied/?msclkid=b913148dd10911ec932962fbfdac1591 [accessed on 24/11/24].

Metz, T. (2015). How the West was one: The Western as individualist, the African as communitarian. *Education, Philosophy, and Theory*, 47(11), pp. 1175-1184.

Myszczynska, M., Ojamies, P., Lacoste, A., Neil, D., Saffaris, A., Mead, R., Hautbergue, G., Holbrook, J., & Ferraiuolo, L. (2020). Applications of machine learning to diagnosis and treatment of neurodegenerative diseases. *Nature Review/Neurology*. Available from: https://doi.org/10.1038/s41582-020-0377-8 [accessed on 24/11/24].

Nettel, P.F., Rogerson, A., Westgarth, T., Iida, K., Mbayo, H., Finotto, A., Rahim, S., and Petheram, A. (2021). *Government AI Readiness Index 2021*. Oxford Insights.

Norgeot, B., Glicksberg, B., Butte, A. (2019). A Call for deep-learning healthcare. *Nature Medicine*, 25(2019), pp. 14-18.

OECD. (2019). Recommendation of the Council on Artificial Intelligence. OECD Legal Instruments. Available from: https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449 [accessed on 24/11/24].

Owoyemi, A., Owoyemi, J., Osiyemi, A., & Boyd, A. (2020). Artificial intelligence in Africa. *Front. Digit. Health*, 2(6), pp. 2-5.

Rajagopal and Rajagopal. (2014). Disruptive innovations and technologies. In: Rajagopal, ed. *Architecting Enterprise*. London: Palgrave Macmillan, 200-222.

Ranka, S., Reddy, M. and Noheria, A. (2021). Artificial intelligence in cardiovascular medicine. *Curr Opin Cardiol*, 36(1), pp. 26–35.

Rieder, G, Simon, J and Wong, P (2020). Mapping the Stony Road toward Trustworthy AI: Expectations, Problems, Conundrums. In: Marcello, P. and Teresa S. eds. Machines We Trust: Perspectives on Dependable AI. Cambridge, MA: MIT Press, pp. 1-14.

Segun, S. (2014). The prefix African and its implication for philosophy in Africa. *Filosofia Theoretica: Journal of African Philosophy, Culture and Religions*, 3(2), pp. 106-123.

Segun, S. (2020). Critically Engaging the Ethics of AI for a Global Audience. *Ethics and Information Technology*. Available from: https://doi.org/10.1007/s10676-020-09570-y [accessed on 24/11/24].

Shearer, E., Stirling, R., Pasquarelli, W., Chung, Y., Cussins, J., Salem, F., Sey, A., Martinho-Truswell, E., Castets-Renard, C., Pichu, R., and Scrollini, F. (2020). *Government AI Readiness Index 2020*. Oxford Insights. Available from:

https://static1.squarespace.com/static/58b2e92c1e5b6c828058484e/t/5f7747f29ca3c20ecb598f7c/1601653137399/AI+Readiness+Report.pdf [accessed on 24/11/24].

Sloane, M. (2022). AI-driven biometry and the infrastructure of everyday life. Available from: https://www.adalovelaceinstitute.org/blog/biometry-and-infrastructures/ [accessed on 24/11/24].

Smith, L. & Neupane, S. (2018). *Artificial intelligence and human development: Toward a research agenda.* White Paper. International Development Research Centre (IDRC). Available from: https://idl-bnc-idrc.dspacedirect.org/handle/10625/56949 [accessed on 24/11/24].

Smith, B. & Shum, H. (2018). *The Future Computed.* Washington: Microsoft.

Topol, E. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nat Med*, 25(2019), pp. 44–56.

Ugar, E. (2022). Artificial intelligence and African normative accounts of personhood. In: De Oliveira, Tauchen, and Castanheira,N (eds.) *Bioethics, neuroethics, & AI ethics in a post-pandemic world*. Porto Alegre: Editora Fundação Fenix, pp. 87-112.

Ugar, E. (2023a). Rethinking remote work, automated technologies, meaningful work, and the future of work: Making a case for relationality. *Philosophy and Technology,* 36(32), pp. 1-21.

Ugar, E. (2023b). The fourth industrial revolution, techno-colonialism, and the Sub-Saharan Africa response. Filosofia Theoretica: *Journal of African Philosophy, Culture and Religion,* 12(1), pp. 33-48.

Van De Poel, Ibo. (2020). Embedding values in artificial intelligence (AI) systems. *Minds and Machines,* 30(2020), pp. 385-409.

Wilkinson, R. (1996). *Unhealthy societies: The afflictions of inequality*. London: Routledge.

Wilkinson, R. (2003). Social determinants of health: The solid facts. Geneva: *World Health Organization Regional Office for Europe*.