Responsible AI in Africa—Challenges and Opportunities

Chinasa T. Okolo, Kehinde Aruleba, and George Obaido

Introduction

Since its inception , the development and integration of artificial intelligence have been mostly concentrated within the Global North. This concentration of power has direct ties to the colonial history of resource extraction from the Global South that deprived nations in this region of autonomy and means to industrialise. This disparity has limited the ability of artificial intelligence applications to be effective, meaning that these tools are able to operate in a functional manner that doesn't compound existing inequities, within such contexts. Effective AI adoption and implementation of artificial intelligence are dependent on a variety of factors, such as having a local workforce with the required training to develop these solutions, sufficient infrastructural capacity to

C. T. Okolo
Cornell University, Ithaca, NY, USA

K. Aruleba
University of Leicester, Leicester, UK

G. Obaido (✉)
University of California, Berkeley, CA, USA
e-mail: rabeshi.george@gmail.com

D. O. Eke et al. (eds.), *Responsible AI in Africa*, Social and Cultural Studies of Robots and AI, https://doi.org/10.1007/978-3-031-08215-3_3

handle the computationally-heavy training of algorithms, representative datasets, governmental support and regulation to govern the appropriate fair use of these technologies, independent and civil institutions and policymakers that safeguard from harmful applications and reinforce responsibility and accountability. Within the African continent, we find these factors sorely lacking and a major contributor to the dearth of solutions implemented that incorporate artificial intelligence. In this chapter, we present a number of challenges to effective AI adoption and implementation in Africa. We examine topics such as digital literacy, infrastructure and government support then lead into an analysis of the AI startup and research landscape within the continent. The chapter then defines what responsible AI looks like for Africa and provides actionable recommendations for improving its progress.

What Signifies Responsible AI

The concept of responsible AI has garnered significant attention in recent years (Boden et al., 2017; Gwagwa et al., 2020; Neri et al., 2020; Arrieta et al. 2020). According to Boden et al. (2017), responsible AI is the tendency of behaving in a positive, desirable, or socially acceptable manner. To formulate a central theme for responsible AI, several organisations created frameworks for building AI responsibly. These organisations formed an organisation termed the Partnership on Artificial Intelligence (PAI).[1] The partnership included organisations such as Amazon, Facebook, Google, Microsoft and IBM. PAI documented best practices to bring diverse organisations together to build AI systems responsibly to benefit the people and society. PAI described responsible AI as an approach geared towards ethical, social consequences that must be considered towards the development and deployment of AI systems.

Succinctly, the goals of the partnership on AI are fourfold:

- First, to develop and share best-practice methods and approaches in the research, development, testing and fielding of AI technologies;
- Second, to advance public understanding of AI across varied constituencies, including on core technologies, potential benefits and costs;

[1] https://www.partnershiponai.org/

- Third, to provide an open and inclusive platform for discussion and engagement on the future of AI, and to ensure that key stakeholders have the knowledge, resources and overall capacity to participate fully in these important conversations; and
- Fourth, to identify and foster aspirational efforts in AI for socially benevolent applications.

AI enables society to automate more tasks and automate to a larger extent than before, but it is important to understand who or what is responsible for the benefits and harms of using this technology? And, if this problem should be tackled pro-actively in the domains of technology and policy, what does the development of "responsible AI" mean? (Coeckelbergh, 2020) To address this question within an African context, we describe the different tenets of responsible AI as mentioned by Nyabola (2016) and Shearlaw (2016), such as accountability, transparency, explicability, transparency and bias.

Principles of Responsible AI

Accountability

One of the common principles of responsible AI discourse is accountability (Arrieta et al., 2020; Raji et al., 2020a; Rakova et al., 2021). According to Raji et al., (2020a), accountability is the state of being answerable or responsible towards a system with its underlying behaviour and its likely impacts. Their work further emphasised that algorithms cannot be held accountable. They are not legal entities; the organisations using and deploying these algorithms should be held liable through governance structures.

Within the tenets of the law, the notion of responsibility is often coupled with liability and punishment for misdeeds, with accountability viewed as a review, oversight and enforcement (Kohli, 2018). In their work, Doshi-Velez (2017) noted that creating accountable AI systems is crucial because accountability is essential for good public and private governance. Ensuring accountability in AI systems requires guiding actions and providing explanations in line with social values and norms. To ensure accountability, Africa needs stringent policies to govern AI usage to ensure rights preserving and ethics in its formative design (Gwagwa et al., 2020). While only a few African countries have established data protection laws, many remain apathetic about it.

Transparency

Transparency means different things to different people, a term poignantly described by Weller [22]. Towards an AI discourse, Hollanek (2020) noted that a transparent system would provide information of what it is doing and why, and it must be permissible to be audited. Current AI algorithms are black boxes. The unboxing of AI algorithms has shown to be an engineering challenge, requiring clarity and explanations for end-users and regulators. This level of opacity is seen as surreptitious, incorporated by complex data processing, purported as a matter of deliberate practice (Hollanek, 2020).

Within contemporary African settings, the lack of AI transparency is visibly apparent (Gwagwa, 2020). One notable example is surveillance technology, where many African states are deploying these systems to monitor citizens (Mudongo, 2021). Most foreign organisations predominantly run these systems with the sole purpose of achieving political agendas or silencing critics. Such lack of transparency infringes user's privacy and leads to data exploitation. According to Hollanek (2020), to assess AI transparency, one must recognise that the developer has always been a trickster, applying masking techniques to achieve a result. The gateway to transparency is to ensure that all aspects of algorithm design, politics and morals have to be considered, especially to win trust.

Explicability

We used explicability and explainability interchangeably. The concept of explainability is viewed as the notion of explanation of steps taken by an AI model, in an attempt to ensure transparency, such that the result produced must be clearly understood by a human expert (Neri et al., 2020; Arrieta et al., 2020). For example, in precision medicine, medical practitioners require much more information from an AI model about a medical diagnosis rather than just some binary predictions. Other notable application areas that require explanations include autonomous vehicles, security, finance, among others.

According to Carman and Rosman (2021), to develop AI models sensitive to African interests and values, it is pertinent to adopt the principle of explicability relevant in an African research context. The authors echoed that for an African adoption, AI systems must be just, fair and intelligible. The study further recommended that AI frameworks be designed to be applied to an African context for transparency. Regrettably, as a continent with diverse cultures and values, it is widely understood that African interests are not considered during AI designs (Wareham, 2021).

Bias Evaluation

AI bias occurs when an algorithm's output becomes prejudiced due to false assumptions based on the data fed into it (Silberg, 2019). Silberg argued that the extent to which AI is used for prediction and decision-making will always be subject to bias challenges. Roselli et al. (2019) argued that AI biases stem from diverse sources, such as the chosen algorithm, input attributes and training data used. Several AI biases have been seen in diverse applications, such as facial recognition systems, autonomous vehicles, health systems, criminal justice systems and recruiting systems (Mehrabi et al., 2021; Perkowitz, 2021; Gebru, 2020; Jo & Gebru, 2020). A typical example of AI bias in the medical field might be that an algorithm may wrongly recognise doctors as male and not female or exclude minorities. In some cases, AI systems may falsely misclassify a black person as a criminal element before standing trial or even likely to re-offend. Such systems often exclude traditionally marginalised groups and result in many diversity issues.

There has been growing use of AI in many sectors in Africa, especially in an unequal society, such as South Africa. Most banks use such technologies to make loan decisions (Adams et al., 2020). However, the metric used for allocating loans through demographics or loan history is widely unavailable. Such systems may be used to disadvantage certain races or genders. Moosajee (2021) attributes this issue to biased results caused by biased data.

Challenges to Effective AI Adoption and Implementation in Africa

In this section, we present the challenges towards AI adoption and implementation in Africa.

Digital Literacy

Digital skills literacy is a significant barrier to the adoption and implementation of artificial intelligence in Africa. Out of all world regions, sub-Saharan Africa has the lowest percentage of citizens equipped with digital skills, equalling to about half of the average level of digital skills adoption seen globally (Madden & Kanos, 2021). The Future of Work in Africa 2021, a report from the World Bank, shows that, on average, citizens in Nigeria, Kenya and South Africa possess a higher level of digital skills compared to the rest of sub-Saharan Africa (Choi et. al 2020). Inspired by the Sustainable Development Goals formed by the UN, the World Bank has formed the Digital Economy for Africa (DE4A) initiative, to digitally enable every African individual, business and government by 2030 (World Bank, 2021). Creating building blocks for a digital economy within the African continent shows promise in enhancing economic growth and alleviating poverty by encouraging entrepreneurship among young adults, increasing farming productivity and yields, and balancing the labour workforce by creating pathways for women to access more jobs (World Bank, 2019a, b). While some of the statistics presented earlier in this section seem dismal, it is important to note the historical and structural issues that have led to such outcomes. Historically, the lack of investment by African governments into infrastructure necessary for supporting digital economies has hampered the growth of digital literacy. With the help of international finance institutions and intergovernmental organisations, countries such as Mozambique and Rwanda have actively begun to develop action plans towards achieving digital transformation (World Bank, 2021). Over the past few years, large technology companies have begun to realise the importance of training local workforces in digital skills. In May 2021, Microsoft announced a partnership with the Nigerian government to significantly build their digital economy (Microsoft, 2021). This collaboration plans to speed Nigeria's transition to becoming a digital economy by making significant investments in internet infrastructure, equipping 5 million people across the country with digital skills, developing cloud-based tools to fight corruption and leveraging artificial intelligence to preserve cultural heritage. With companies such as Microsoft, Twitter, IBM, Facebook and Google already having such a large presence within the African continent, commitments such as the one seen by Microsoft can help subvert the colonial narratives and dynamics seen in other industries like agriculture and mining. However, their presence is not without great scrutiny or concern. Big Tech is not the saviour Africa needs to look up to and their presence in Africa is driven primarily by profits, monopoly and a rush to grab power more than anything else.

Infrastructure

Over the past decade, internet penetration within the African continent has risen rapidly from an estimated 10% in 2010 to 28% in 2019 (ITU, 2021). The sore state of internet penetration across the African continent can be blamed due to infrastructure issues associated with the lack of access to electricity and low investment into internet infrastructure such as fibre-optic cables, cell towers and base stations. According to the World Bank, 80% of the urban population in sub-Saharan Africa has access to electricity compared to 28% in rural sub-Saharan Africa[2]. The World Bank estimates that reaching the 100 million Africans living in remote regions inaccessible to cellular mobile networks will require an investment of at least $100 billion[3]. While an extremely large number, tech companies such as Google, Facebook and Microsoft have lent their expertise and vast financial resources to improve internet infrastructure across Africa and the Global South to varying levels of success. Alphabet's (Google's parent company) Loon, a project developed in 2011 to bring high-speed internet to remote regions through fleets of balloons, operated in regions such as Sri Lanka, Puerto Rico, Mexico, Brazil, Chile, Argentina and Kenya (Loon, 2017). While this project was disbanded in early 2021, Alphabet has pledged $10 million to support companies and organisations focused on internet connectivity, education and entrepreneurship within Kenya (Teller, 2021). In partnership with Samsung, Ericsson, MediaTek, Opera, Nokia and Qualcomm, Facebook

[2] https://data.worldbank.org/indicator/EG.ELC.ACCS.RU.ZS?locations=ZG&name_desc=false

[3] https://www.worldbank.org/en/news/press-release/2019/10/17/achieving-broadband-access-for-all-in-africa-comes-with-a-100-billion-price-tag

launched Free Basics (also known as Internet.org), an initiative to provide free internet services to underdeveloped countries in 2013[4]. This service provides free internet access to websites containing job ads, weather and health information and full access to the entire internet for those who pay. This two-tiered system has been criticised for harming net neutrality and cannibalising the services of local internet cafes, leading to its eventual shutdown in India (Prasad, 2018). To this date, 32 African countries have participated in this initiative but over the past decade, internet shutdowns have become a common censure tactic for African governments (Killander & Ilori, 2020). The close relationship between Free Basics and the telecommunication companies providing these services, many of which are fully or partially state-owned, is a troubling issue that should be examined more closely. In 2020, Facebook announced "2Africa", their billion dollar project to build an undersea cable that will interconnect 23 countries in Africa, tripling the continent's existing network capacity and providing support for 4G, 5G and broadband access (Facebook Engineering, 2020). Microsoft Airband, launched in 2017 to bring internet connectivity to rural regions, currently has projects in 8 African countries (Ghana, Nigeria, Kenya, South Africa, Democratic Republic of Congo, Zambia, Tanzania and Rwanda)[5]. While Africa continues to be the focus point of internet-related initiatives, there is reasonable scrutiny of these initiatives and their capabilities to exacerbate existing censorship of citizens by African governments and introduce new methods of surveillance to the continent (Shearlaw, 2016).

Price Barriers

The Global System for Mobile Communications estimates that 45% of the population in sub-Saharan Africa subscribes to mobile services (GSMA, 2020). Affordability is a large barrier to preventing the adoption of both mobile devices and services, which is the primary way users within the African continent access the internet. Another factor that impacts affordability is the high telecommunications taxation rates in countries such as the Democratic Republic of Congo, Mozambique, Sierra Leone and Tanzania, which are above the world average (GSMA, 2016). The

[4] https://connectivity.fb.com/

[5] https://www.microsoft.com/en-us/corporate-responsibility/airband

majority of low- and middle-income countries have failed to meet affordability targets set by the Alliance for Affordable Internet (A4AI) and adopted by the UN Broadband Commission for Sustainable Development (Policy, 2018). When represented as a percentage of average per capita Gross National Income (GNI), the average price of one gigabyte of mobile broadband varies between 0.84% in North America and 17.49% in Africa (Policy, 2018). With an average cost of $3.30 per gigabyte of mobile internet—a price that is higher than anywhere in the world except for North America[6]—African consumers are being priced out of access to the internet and stonewalled from improving their livelihoods through digital means. African governments have to be proactive in regulating large, multinational telecom companies in setting fair prices for consumers and providing the necessary investments in both electrical and internet infrastructure to accelerate the adoption of digital skills, which will hopefully have a significant impact on the state of AI development within the continent.

Lack of Local AI Talent

While the technology ecosystem within Africa has grown significantly, there is still a large gap between the pace of software development and AI development within the continent. Fortunately, the interest of outside entities like Google, Microsoft and IBM has led to the establishment of AI research labs on the continent and the local startup ecosystem has also begun to grow. Something we find extremely promising is the emergence of local AI practitioners and research groups that have formed to address local problems in agriculture, healthcare, education and more. Initiatives, such as Bhala, a smart keyboard that is the first mobile application to support spell-checking Ndebele, Shona, Swati, Swahili, Xhosa, and Zulu, is an example of home-grown technology that meets the needs of local populations and fills a gap overlooked by larger players in this space[7]. A subsequent section in this chapter (survey of the landscape of AI in the continent) provides a deeper look into the current state of artificial intelligence within the African continent. We analyse over 100 startups and

[6] https://www.dw.com/en/why-mobile-internet-is-so-expensive-in-some-african-nations/a-55483976

[7] https://www.bha.la/about.html

organisations dedicated to providing AI products, services and education and note trends that show great promise or bring cause for concern.

Artificial intelligence has become nearly ubiquitous in many societies and many tech companies have begun to recognise the importance of democratising the development of artificially intelligent systems and providing equitable access to regions traditionally overlooked in AI development. Large tech companies such as Google, Microsoft, IBM, Facebook and Amazon have made strides to move into the Global South, establishing research labs, development centres, customer support centres, or data centres within this region. The openings of these establishments may initially appear to be beneficial for local ecosystems, but the talent needed to fill these highly specialised roles may not exist locally. This presents room for displacement of local workforces by those who have had the privilege to access relevant training and mirrors systems of colonialism.

Fortunately, the past five years has given rise to grassroots efforts focused on training local communities in artificial intelligence and related technologies such as natural language processing (NLP), computer vision and machine learning. Black in AI[8], a nonprofit organisation founded in 2017, has provided hundreds of Black students and professionals the opportunity to attend top tier machine learning conferences such as Conference on Neural Information Processing Systems (NeurIPS), the International Conference on Learning Representations (ICLR), International Conference on Machine Learning (ICML) and much more. Additionally, the organisation has begun mentorship programmes to guide prospective applicants to graduate programmes in computer science, support current PhD students in their journeys towards tenure track positions in academia and provide resources for entrepreneurs of African descent to build successful AI startups. Other prominent initiatives such as Data Science Africa[9], Masakhane[10], Ghana NLP[11], AI Saturdays Lagos[12] and Deep Learning Indaba[13] have similar missions, contributing greatly to the representation of African scholars at AI/ML conference venues,

[8] https://blackinai.github.io/#/

[9] http://www.datascienceafrica.org/

[10] https://www.masakhane.io/

[11] https://ghananlp.org/

[12] https://aisaturdayslagos.github.io/

[13] https://deeplearningindaba.com/2021/

increasing the number of publications focusing on AI and its applications to local problems and improving access to AI education. Another step to improving AI adoption within the African continent has focused on building institutions to formally train students in the concepts needed to pursue successful careers within this field. The African Institute for Mathematical Sciences (AIMS) was launched in 2003 in South Africa to teach specialised topics in the mathematical sciences such as applied mathematics, bioinformatics, scientific computing, artificial intelligence and more[14]. Since then, AIMS has expanded to Senegal, Ghana, Cameroon, Tanzania and Rwanda, graduating nearly 2000 students. To meet the demand for artificial intelligence practitioners within the continent, AIMS launched the African Masters in Machine Intelligence (AMMI) with sponsorship support from Facebook and Google[15]. DeepMind, a subsidiary of Google that develops AI systems to advance scientific discovery, has recently funded scholarships for students to pursue Master degrees in Computer Science with specialisations in AI, ML and data science at Makerere University in Uganda (Mwamai, 2021)[16]. We believe that industry-academic partnerships between local African institutions are a tangible step in bridging the AI-talent gap within the continent and will help build sustainable pathways to encourage future growth. While governments should be taking on the primary responsibility of funding AI education and entrepreneurship, the support of large industry players has helped fill this gap.

Datasets

Another issue plaguing the effective adoption of artificial intelligence in Africa is the lack of data accessible to African researchers and the relevance of this data to African problems in domains such as agriculture, health care and voice/text recognition. Machine learning relies on vast amounts of data to train algorithms, and if this data is sparse and unrepresentative, the resulting algorithms will be less effective and could cause harm to the vulnerable populations. Within Western countries like the

14 https://nexteinstein.org/

15 https://aimsammi.org/about-ammi-2/

16 http://cs.mak.ac.ug/news/view/18

United States, issues regarding dataset representation of minority populations like Black people and women have gained prominence over the past few years (Buolamwini & Gebru, 2018). However, this conversation has continued to stay focused on dataset bias in the context of Western issues, centring the gaze of these problems on the Global North. 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 in the Global South. We find that expanding issues of dataset bias to factors like ethnicity, tribal affiliations and other cultural nuances will help datasets becomes truly inclusive and relevant to solving African challenges. Open-source platforms like Kaggle[17], openAFRICA[18] and Zindi[19] have been supportive avenues for African researchers and AI practitioners to curate and share their datasets, helping to address the lack of datasets within the African continent. Initiatives like the Inclusive Images Challenge from Google[20] have aimed to improve representation of imagery from the Global South, but haven't fully represented the vast diversity within the African continent. This stresses the importance of local communities within the African continent being involved in the creation, sharing and use of datasets. More notably, we find that the formation of grassroots efforts throughout the continent has helped make significant strides in the types of data representing a variety of cultures, languages and regions throughout the continent. Collaborations between entities like Zindi and AI for Development (AI4D) led to the creation of the AI4D Africa Language Challenge in 2020 where over 400 data scientists enrolled to contribute their expertise to build novel datasets[21]. The winners of the challenge submitted datasets encompassing a variety of African languages like Wolof, Igbo, Hausa, Fongbe, Ewe, Kabiye, Kiswahili and Chichewa, many of which aren't present on popular translation services provided by Apple and Google. Other initiatives like the Lacuna Fund[22], which was founded to provide researchers and scientists in low-income countries resources to

[17] https://www.kaggle.com/tags/africa

[18] https://africaopendata.org/dataset

[19] https://zindi.africa/

[20] https://www.kaggle.com/c/inclusive-images-challenge

[21] https://zindi.africa/competitions/ai4d-african-language-dataset-challenge

[22] https://lacunafund.org/about/

produce labelled datasets, have helped improve dataset representation in agriculture, health and languages. More notably, the Lacuna Fund stresses adherence to practices in ethics and privacy, ensuring that the datasets will be owned by their respective creators and openly accessible to the international community. We believe that it is imperative for African researchers to maintain agency over the data they collect and have input on how this data should be shared. Data sharing practices within the African context have been understudied, but a recent paper titled "Narratives and Counternarratives on Data Sharing in Africa" provided much-needed insight on local practitioners involved in these efforts and contributes tangible suggestions towards making datasets context-aware and ensuring the process of collection and sharing is trustworthy (Abebe et al. 2021). While there is still a long way to go in improving the quality and accessibility of datasets representing the African continent, significant progress has been made thus far.

Government Support

Over the past few years, governments have raced to develop legislation that will govern the use and implementation of artificial intelligence for personal and commercial use. However, African governments lag heavily behind those in North America and the European Union. In the 2019 Government AI Readiness Index published by Oxford Insights, Africa is the worst performing region, with no countries listed in the top 50 spots and only 12 in the top 100 (Readiness, 2019). The top five countries who are represented in the top 100 (Kenya, Tunisia, Mauritius, South Africa and Ghana) already have significantly developed tech ecosystems. This brings cause for concern to smaller economies within the African continent who have not developed legislation but could still be impacted by the effects of artificial intelligence. While it is unclear how many African countries have formally instituted regulation on AI, countries like Senegal, Kenya and South Africa have launched regulatory frameworks, data protection laws and acts regulating automated decision-making (Adams, 2021). The Index of Regulation of Artificial Intelligence has monitored the AI policy and regulatory landscape around the world, reporting eight African countries (Ghana, Kenya, Nigeria, Sierra Leone, South Africa, Uganda, Zambia and Zimbabwe) as making strides towards regulating AI (Goitom, 2019). Additionally, the lack of AI legislation proposed by African governments is mainly due to policymakers with scant technology expertise, and insufficient expertise in AI and related emerging technologies. As the local AI workforce grows within the African continent, it will be important that governments provide opportunities for highly-experienced professionals to contribute to AI legislation by serving on technical advisory panels or being placed in government positions specifically developed to leverage their expertise. The development of artificial intelligence in Western countries has been fuelled by local startups and a similar model could prove successful in Africa. Larger companies like Google, Apple and Amazon have made dozens of acquisitions of AI startups over the past few years, but this model may not be efficient for the African context since there is so little AI activity occurring in comparison with the West. Thus, government support for AI startups and research hubs is crucial. This will ensure that local interests and not those of multinational corporations are prioritised when it comes to solving issues with AI and that the continent doesn't experience an "AI brain drain" seen in other fields such as medicine and engineering. Efforts like the Artificial Intelligence Hub at the University of Lagos run by Data Science Nigeria, which is the first of its kind in Nigeria and likely in the continent, provide free AI courses and research labs for aspiring AI practitioners (Ndiomewese, 2018). While it is not clear how much governmental support this initiative received, it is a good model for governments to follow in establishing nationwide AI hubs. Again, we stress the importance of AI development being "for Africans by Africans" to ensure that colonial cycles of extraction by Western entities and historical dependence on foreign aid don't impede what could be a viable pathway towards economic freedom (Chan et al., 2021).

Survey of the Landscape of AI in the Continent

The AI startup and research organisational landscape in Africa has rapidly increased over the past decade and continues to grow. We collected data on 102 African startups and research organisations that are either in operation, defunct, or with an unknown operating status across 11 African countries. Startups and research organisations were included if they operated within any of the 54 countries on the African continent and if their core product or business offering focused on artificial intelligence and/or its respective applications across a variety of domains. As some startups had either expired or broken links to their respective websites, we still included them but listed their operating status as either Unknown (U) or

No (N). Our search for African companies and organisations working with AI was conducted through Google, LinkedIn, Twitter and startup market intelligence platforms like Crunchbase, Pitchbook, Venture Capital for Africa (VC4A) and Tracxn. We also relied heavily on curated lists from sources such as Briter Bridges[23], a business intelligence company focusing on markets in the Global South and AI Expo Africa. This list is not exhaustive but represents a significant number of companies developing artificial intelligence solutions across the African continent.

Companies and organisations operating on the continent span a wide range of industries and domains. From the startups we listed, we found 30 different industries they operate in. Finance, health care, agriculture and research were the largest segments, accounting for nearly 50% of all the companies. Within many startups on the continent, the financial sector has been a priority, and as the shift to AI-powered solutions has begun, there is no surprise that this trend has moved towards finance as well. However, despite the goal of many fintech startups on the continent to improve financial access, they might in fact not be improving the lives of people at the bottom of society. We also find similar trends in health care, where AI has claimed to either match or even exceed the diagnostic capabilities of doctors (Liu et al., 2019). However, this claim only holds true in the high-resourced environments these technologies are developed and tested in, which mostly happen to be in Western societies. As infrastructure within the African continent has scaled rapidly, we expect to see AI being leveraged further across a variety of domains. While AI being applied to fields such as agriculture, health care and finance may help improve overall access to these vital services, if not developed properly, they could indeed exacerbate existing inequities.

A significant number of companies have sprung up as consultancies to help larger businesses incorporate AI strategy into their current respective solutions. These companies were also classified as "AI" companies for the sake of simplicity. Another growing trend we see is the establishment of research groups and initiatives to train AI researchers on the continent and to tackle gaps within AI development that fail to include African users. Groups such as Masakhane[9] have conducted novel research to build datasets and machine translation tools for African languages while

[23] https://briterbridges.com/

other initiatives such as Datascience Nigeria[24] have democratised access to AI education by hosting bootcamps, summits and online competitions. A small number of AI developers on the continent have begun to develop their own libraries to improve AI and data science methods, with some like DeepQuest AI[25] by brothers Moses and John Olafenwa having thousands of users around the world.

The startups in our analysis operate across a total of 11 African countries, with a majority of them based in Nigeria (25%) and South Africa (33%). Compared to other regions within the African continent, Western Africa and Southern Africa have 35 and 33 organisations respectively focusing on AI. Most notably, we find that countries from Francophone Africa (Benin, Burkina-Faso, Cape Verde, Côte D'Ivoire, Democratic Republic of the Congo, Republic of Guinea, Madagascar, Mali, Mauritania, Niger, Senegal, Togo and Tunisia) are missing from the AI ecosystem. While the overall startup and research landscape in AI within the African continent are promising, it is essential that AI services built on the continent include Africans from a diverse set of backgrounds and regions. We find that the artificial intelligence startup ecosystem in Africa is relatively young. All of these startups and organisations were founded between 2010 and 2020, with 72 (70%) of them founded within the past five years. Additionally, almost 80% of the startups in our analysis are early-stage, showing significant room for these companies to grow. While artificial intelligence has been around for decades, we presume that many of the companies in our analysis that were founded in the early 2010s may have adjusted their respective strategies to incorporate AI methodologies.

A majority of the AI solutions developed by startups within the African continent cater to businesses that are aiming to improve their respective AI offerings or introduce AI into their operational systems. As financial technology (also known as fintech) becomes increasingly popular, we find that a significant number of AI startups are developing technology to improve banking processes or make financing decisions for customers based on existing data. Agricultural businesses and healthcare facilities are also popular options for AI startups to provide services for these industries that are rapidly digitising. Our analysis notes a growing trend of AI being

[24] https://www.datasciencenigeria.org/

[25] https://deepquestai.com/

introduced into warehouse operations and for manufacturing capabilities which could prove positive in scaling growth in these sectors and having a positive economic impact.

Out of 102 startups, 22 of them (21%) had either all white or majority white/non-African founding teams. Many of these companies were based in South Africa, which we find particularly concerning due to the types of technologies such as facial recognition being developed by these startups which would disproportionately affect a major part of the respective population. In the United States, research has shown how facial recognition systems from companies such as Microsoft, IBM, Amazon and others are biased against subjects of darker skin tones and those with female characteristics (Buolamwini, 2018). These companies have either chosen to improve the gender and racial makeup of the datasets used to train these systems or abandon facial recognition technology altogether (Heilweil, 2020). Surveillance technologies like facial recognition are being deployed within large cities throughout the continent and have received major backlash from citizens in countries like South Africa and Zimbabwe, but continue to stay in use (Chutel, 2018; Hawkins, 2018). This again raises concern due to policing systems in countries such as South Africa that are significantly biased towards Black South Africans who make up a considerable portion of the population.

From the 102 startups we analysed, we found that there is a lack of information and transparency on what exactly most startups are doing: what methods they are using to build their predictive models, where their data is sourced, and how well their models perform. These issues have been characterised as fairness, accountability, transparency and ethics (FATE) and dozens of startups, mainly in the United States and Europe, have formed to address these issues of data and model observability. As this field continues to widen, it will be important for African startups working with AI technologies to construct AI observability platforms of their own or work with other local startups in this space. More significantly, it is hard to conclusively say if there is a "true" AI element within many of the startups we ed. However, this is an issue that is not relegated solely to startups within the African continent. In 2019, London venture capital firm MMC studied almost three-thousand "AI startups" across the EU, concluding that 40 per cent of these companies do not incorporate artificial intelligence in their products (MMC, 2019). The overuse of the phrase "artificial intelligence" has led to unrealistic exaggerations of technology and excessive trust on what AI can do. Academic research labs and

AI startups have purported to build AI systems that can detect emotions, gender, sexuality and even political orientation; however, these tasks are nearly impossible for a human to accomplish (Birhane, 2021; Heckman, 2020; Wojcik & Remy, 2019). This work has led to calls for the EU to ban these tools (Asher-Schapiro, 2021) and we hope that policymakers within the African continent recognise these harms and actively begin to introduce regulation banning these tools. With the business models of many of these types of companies primarily being motivated by maximising profit at any cost, the autonomy and well-being of everyday citizens should not be disregarded. Current AI technologies are already believed to cause harm to marginalised people around the globe, and as AI grows within the African continent, there could be repercussions if its development isn't well-governed.

Emerging Trends and Concerns in AI Deployments in Africa

China is making a push for AI leadership and doubling down on its soft power initiatives in Africa as part of China's Grand Strategy to tap emerging markets, shape global governance norms and expand its influence (HDI, 2021; Nantulya, 2018). In his report to the 19th Party Congress in October 2017, Chinese President Xi Jinping outlined his vision for China becoming a global science and technology leader by 2050 (Shepherd & Qiu, 2017). A growing consensus singles out China as a major driver and influencer of authoritarian tech (Feldstein, 2019a, b). Several experts have claimed that Chinese governments are working closely with Chinese companies to export authoritarian tech to like-minded governments to promote an alternative governance model (Polyakova & Meserole, 2019; Sharma, 2020; Mozur et al., 2019). These reports can be validated with the recent increase in the export of Chinese tech, which are gross human rights violators to countries such as Zimbabwe, Uganda and Ethiopia (Feldstein, 2019a, b). Most of the countries in Africa rely on Chinese companies for their digital and telecom services. For example, the Ethiopian government uses the services and infrastructures of ZTE, a Chinese telecom to monitor its citizens' communications, Hikvision, the world's leading surveillance camera manufacturer, recently opened an office in Johannesburg, CloudWalk Technology, a startup based in Guangzhou, recently signed a deal with the

Zimbabwean government (Hawkins, 2018), and Transsion a Shenzhen-based company that has never sold a handset in its native China, but its brands iTel, Tecno and Infinix sell more smartphones than any other produces in Africa (Bayes, 2019; Bloomberg, 2018).

As reported in the AI Global Surveillance (AIGS) Index, Chinese companies led by Huawei are leading the supply of AI technologies with much focus on surveillance systems around the world (Feldstein, 2019a, b). Huawei technology has been linked to more countries in the South than any other company. It is aggressively infiltrating into the sub-Saharan Africa technology market by providing not only equipment and technological tools but also offering operation, management and support to set up these tools. To date, at least 12 African countries are using Huawei digital surveillance technology (Olander, 2019; Jili, 2020). An investigative report in The Wall (2019) highlighted that Huawei employees, technicians, provide other services to Uganda and Zambia governments that are not disclosed publicly. They helped the Uganda government spy on their political opponents by using cell data to track their locations and intercept their encrypted social media and communications. Also, in Zambia, the employees assisted the government in gaining access to Facebook pages and phones of bloggers critical of the president so they could be tracked and arrested. In Uganda, the government splashed $126 million on CCTV from Huawei (Reuters, 2019; Woodhams, 2020). The police say the new CCTV system will help reduce violent crime; however, the opposition leaders and civil society leaders believe that the law enforcement bodies are overburdened and too corrupt to identify criminals using footage. They believe the cameras with facial recognition technology will target and identify demonstrators in violent clampdowns as the election approaches in 2021.

Facial recognition technology has become increasingly pervasive around the world today, with the rising concerns about privacy, potential abuses, security, bias and freedom (Zeng et al., 2019); this has led to cities such as San Francisco ban its usage (Conger, 2019). In 2018, the government of Zimbabwe employed a surveillance network developed by CloudWalk to provide a mass facial recognition programme. In exchange for the technology, Zimbabwe sends images of its citizens, which give China an edge in AI technologies compared to other Western countries (Mind Matters News, 2020; Techzim, 2018). Beyond the human rights concerns, the deal pointed to another angle to the China-Africa tech story: the quest for technological advantage. As one local outlet put it:

"the Zimbabwe Government is sending our faces to China so China's AI can learn to see black faces". Existing AI facial recognition technologies are principally trained on white and East Asian datasets; the Zimbabwe deal offered Cloudwalk valuable data for improving its recognition of other ethnicities—thereby strengthening the arsenal of surveillance tools available to authoritarian governments (Bayes, 2019).

> Its terms require Harare [the capital of Zimbabwe] to send images of its inhabitants—a rich data set, given that Zimbabwe has absorbed migration flows from all across sub-Saharan Africa—back to CloudWalk's Chinese offices, allowing the company to fine-tune its software's ability to recognize dark-skinned faces, which have previously proved tricky for its algorithms.—Andersen (2020a, b)

By expanding into African markets, China's tech companies are gaining access to that sought-after commodity, data. Yes, these companies are playing a positive role in connecting African citizens, consumers and businesses. Nevertheless, they also have another role in helping Beijing promote its model of the internet as a controlled space and as a data-driven instrument of social and political control.

As reported by Tilouine and Kadiri (2018), the Africa Union (AU) building headquarters at Addis Ababa gifted to AU by China was serving the Chinese government more purpose than initially assumed. In January 2018, AU officials accused China of hacking its headquarters computer every night (when no one was in the office, but daylight had broken in Shanghai) for five years and downloading confidential data. Beijing had funded the building in Ethiopia, and a Chinese state-owned company built it. Chinese workers still maintain the building to this day, and even its elevator symbols are written in Chinese. This is bothersome. That one of the most prominent political organisations in the continent had been unknowingly sending all of their confidential data directly to the Chinese state certainly raises concerns about the implications of China's growing influence in the technological infrastructure of Africa. The overt Chinese presence on the continent in construction, technology and business has been attributed to the availability of generous loans with affordable interest rates and willing partnership for development (Future Africa,2018).

Recommendations for Improving Responsible AI Progress in Africa

According to Feldstein (2019a, b), local governments have the right to undertake surveillance systems that are unbiased and rooted in limiting their citizens' freedom and enforcing political repression. For example, tracking technologies play a crucial role in preventing terrorism. They give the government the ability to monitor threats and act accordingly. Governments can also use face recognition tools in finding missing people and victims of human trafficking. However, technology and power struggles have changed the nature of how governments use surveillance systems and what they intend to monitor. Generally, the legal standards required to utilise surveillance systems legitimately are high, and governments find it challenging to meet them. Countries with weak legal enforcement or authoritarian systems "*routinely neglect these obligations*" (Feldstein, 2019a, b).

Several authors have investigated the implication of racial bias surveillance and facial recognition algorithms (Cavazos et al., 2020; Bacchini & Lorusso, 2019; Raji et al., 2020b; Seutloali, 2015). Despite all the identified implications and recommendations made by these authors, it is important to state that no algorithm improvement is safe from the risk of contributing to racial discrimination if the social context in which it unfolds mainly consists of racial prejudice. A key recommendation is to stop seeing face recognition technologies as tools that do not see race and focus on working hard to monitor and get rid of racist from these tools. We need software and systems trained on datasets that are equally made up of faces representing all races. Until a solution to bias is found, algorithms need to be tested regularly for racially biased error rates.

Awareness is also a key precondition. We cannot hope that any of these recommendations are ever achieved unless we become definitively aware that facial recognition technology is doomed to be racially biased—at least until racism is permanently erased. Of course, the most effective recipe for a racism-free face recognition technology is to struggle for a racism-free society.

It is crucial to align AI initiatives and the data used for training AI models to local communities in Africa and the Global South in general. Engaging these communities, offering training solutions, understanding local issues and their unique needs will help create an avenue for developing more inclusive AI technology.

Conclusion

As AI development extends across the world and begins to make significant progress within Africa, it is imperative that local development of AI is encouraged and actively supported by governments, international agencies and large tech companies who have already begun to expand their global footprint throughout the continent. With current discourse and development of artificial intelligence focused on the West and China, there is little work that understands the nuances and sociotechnical implications of AI development in Africa. Combined with the lack of policy regulating the use of AI in many African countries, some of which has been problematic, Africa remains ripe for continued exploitation through new avenues presented by AI.

Although it will take considerable effort and expense to grow African countries into "AI superpowers", leveraging existing strengths in the software development and AI research communities while investing in infrastructure are viable steps towards this goal. AI has strong potential to transform livelihoods within Africa, but it is up to the continent to diligently focus on ensuring the potential risks and harms of AI don't outweigh the benefits.

References

Abebe, R., Aruleba, K., Birhane, A., Kingsley, S., Obaido, G., Remy, S.L. and Sadagopan, S., 2021, March. Narratives and counternarratives on data sharing in Africa. In Proceedings of the 2021 *ACM Conference on Fairness, Accountability, and Transparency* (pp. 329–341).

Abiodun, F, (2018). 'Developing Public Sector Leaders for Africa: So China is Spying on the African Union? Who is Surprised?', *Future Africa*, 30 January. Available at: https://futureafrica.net/so-china-is-spying-on-the-african-union-who-is-surprised/ (Accessed: 11 June 2021).

Adams, R., Fourie, W., Marivate, V. and Plantinga, P., 2020. Introducing the series: can AI and data support a more inclusive and equitable South Africa? *Human Sciences Research Council*.

Adams, N.-R. (2021) 'AI law and Afrofuturism—how to regulate AI's future in Africa', *Michalsons,* 11 February. Available at: https://www.michalsons.com/blog/ai-law-and-afrofuturism-how-to-regulate-ais-future-in-africa/47558 (Accessed: 11 June 2021).

Aliya, R. (2019) 'Europe's AI start-ups often do not use AI, study finds', *Financial Times,* 4 March. Available at: https://www.ft.com/content/21b19010-3e9f-11e9-b896-fe36ec32aece (Accessed: 11 June 2021).

Alliance for Affordable Internet. (2018a) 'UN Broadband Commission Adopts A4AI "1 for 2" Affordability Target', *News Archives—Alliance for Affordable Internet*, 23 January. Available at: https://a4ai.org/un-broadband-commission-adopts-a4ai-1-for-2-affordability-target/ (Accessed: 10 June 2021).

Alliance for Affordable Internet. (2018b). *Affordable Internet Access: The cost challenge*. Available at: https://a4ai.org/affordable-internet-access-the-cost-challenge/ (Accessed: 11 June 2021).

Andersen, R. (2020a) 'Chinese AI Is Creating an Axis of Autocracy', *The Atlantic, 1 September*. Available at: https://www.theatlantic.com/magazine/archive/2020/09/china-ai-surveillance/614197/ (Accessed: 11 June 2021).

Andersen, R. (2020b). The panopticon is already here. Available at: https://www.theatlantic.com/magazine/archive/2020/09/china-ai-surveillance/614197/ (Accessed: 10 June 2021).

Arrieta, A.B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R. and Chatila, R., 2020. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, pp. 82–115.

Asher-Schapiro, A. (2021) 'EU urged to ban "discriminatory" AI tools that detect gender or sexuality', *Reuters*, 16 April. Available at: https://www.reuters.com/article/eu-tech-lgbt/eu-urged-to-ban-discriminatory-ai-tools-that-detect-gender-or-sexuality-idUSL8N2M86XH (Accessed: 11 June 2021).

GSM Association. (2016) *Connected Society Consumer Barriers to Mobile Internet Adoption in Africa*. Available at: https://www.gsma.com/mobilefordevelopment/wp-content/uploads/2016/07/Consumer-Barriers-to-mobile-internet-adoption-in-Africa.pdf (Accessed: 10 June 2021).

GSM Association. (2020) *Sub-Saharan Africa 2020 The Mobile Economy*. Available at: https://www.gsma.com/mobileeconomy/wp-content/uploads/2020/09/GSMA_MobileEconomy2020_SSA_Eng.pdf (Accessed: 10 June 2021).

Bacchini, F. and Lorusso, L. (2019), Race, again: how face recognition technology reinforces racial discrimination, *Journal of Information, Communication and Ethics in Society, (17)3*, pp. 321–335. https://doi.org/10.1108/JICES-05-2018-0050

Bayes, T., (2019) 'African networks, smartphones - and surveillance', *Merics,* 18 June. Available at: https://merics.org/en/analysis/african-networks-smartphones-and-surveillance (Accessed: 11 June 2021).

Birhane, A., (2021). The Impossibility of Automating Ambiguity. *Artificial Life*, pp.1–18.

Biryabarema, E. (2019) 'Uganda's cash-strapped cops spend $126 million on CCTV from Huawei', *Reuters*, 15 August. Available at: https://www.reuters.com/article/us-uganda-crime-idUSKCN1V50RF (Accessed: 11 June 2021).

Boden, M., Bryson, J., Caldwell, D., Dautenhahn, K., Edwards, L., Kember, S., Newman, P., Parry, V., Pegman, G., Rodden, T. and Sorrell, T., 2017. Principles of robotics: regulating robots in the real world. *Connection Science, 29(2)*, pp. 124–129.

Buolamwini, J. and Gebru, T., (2018), January. Gender shades: Intersectional accuracy disparities in commercial gender classification. In *Conference on Fairness, Accountability and Transparency* (pp. 77–91). PMLR.

Buolamwini, J. (2018) *Gender Shades*. Available at: http://gendershades.org/ (Accessed: 11 June 2021).

Carman, M. and Rosman, B., 2021. Applying a principle of explicability to AI research in Africa: should we do it?. *Ethics and Information Technology, 23(2)*, pp. 107–117.

Cavazos, J.G., Phillips, P.J., Castillo, C.D. and O'Toole, A.J., 2020. Accuracy comparison across face recognition algorithms: Where are we on measuring race bias?. *IEEE transactions on biometrics, behavior, and identity science, 3(1)*, pp.101–111.

Chan, A., Okolo, C.T., Terner, Z. and Wang, A., 2021. *The Limits of Global Inclusion in AI Development*. arXiv preprint arXiv:2102.01265.

Chen, L. Y. (2018) 'Are you a robot?', *Bloomberg,* 28 March. Available at: https://www.bloomberg.com/news/articles/2018-03-28/this-chinese-phone-maker-has-taken-over-africa-for-better-and-worse (Accessed: 11 June 2021).

Choi, J., Dutz, M.A. and Usman, Z. eds., 2020. *The Future of Work in Africa: Harnessing the Potential of Digital Technologies for All*. World Bank Publications.

Chutel, L. (2018) 'China is exporting facial recognition software to Africa, expanding its vast database', *Quartz Africa*, 25 May. Available at: https://qz.com/africa/1287675/china-is-exporting-facial-recognition-to-africa-ensuring-ai-dominance-through-diversity/ (Accessed: 11 June 2021).

Coeckelbergh, M., 2020. Artificial intelligence, responsibility attribution, and a relational justification of explainability. *Science and Engineering Ethics, 26(4)*, pp. 2051–2068.

Conger, K., Richard, F., and Kovaleski, S. (2019) 'San Francisco bans facial recognition technology', *The New York Times*, 14 May. Available at: https://www.nytimes.com/2019/05/14/us/facial-recognition-ban-san-francisco.html (Accessed: 08 June 2021).

Ding, J. (2018) 'Deciphering China's AI dream', *Future of Humanity Institute,* 14 March. Available at. https://www.fhi.ox.ac.uk/wp-content/uploads/Deciphering_Chinas_AI-Dream.pdf (Accessed 11 June 2021).

Doshi-Velez, F., Kortz, M., Budish, R., Bavitz, C., Gershman, S., O'Brien, D., Scott, K., Schieber, S., Waldo, J., Weinberger, D. and Weller, A., 2017. Accountability of AI under the law: The role of explanation. arXiv preprint arXiv:1711.01134.

Dzoma, G. (2018) 'Zimbabwe Government Is Sending Our Faces To China So China's Artificial Intelligence System Can Learn To See Black Faces', *Techzim,* 8 November. Available at: https://www.techzim.co.zw/2018/11/zimbabwe-government-is-sending-our-faces-to-china-so-chinas-artificial-intelligence-system-can-learn-to-see-black-faces/ (Accessed: 11 June 2021).

Economy, E.C., 2018. China's new revolution: The reign of Xi Jinping. *Foreign Affairs, HeinOnline Journal*. pp. 60–61.

Ehl, D. and Grün, G-C. (2020) 'Why mobile internet is so expensive in some African nations', *DW*, 03 November. Available at: https://www.dw.com/en/why-mobile-internet-is-so-expensive-in-some-african-nations/a-55483976 (Accessed: 11 June 2021).

Facebook Engineering. (2020) 'Building Africa, a transformative subsea cable to better connect Africa', *Meta Engineering 13 May,* Available at: https://engineering.fb.com/2020/05/13/connectivity/2africa/ (Accessed: 10 June 2021).

Feldstein, S., 2019a. The global expansion of AI surveillance (Vol. 17). Washington, DC: *Carnegie Endowment for International Peace*.

Feldstein, S., 2019b. Can a UN Report Help Rein in Expansive and Abusive Digital Surveillance?. *World Politics Review*.

Gebru, T., 2020. Race and Gender. *The Oxford handbook of ethics of AI*, pp. 251–269.

Goitom, H., (2019), 'Sub-Saharan Africa', Regulation of Artificial Intelligence in Selected Jurisdictions. pp. 129–131.

Greitens, S.C., 2020. Dealing with Demand for China's Global Surveillance Exports. *Brookings Institution Global China Report*.

Gwagwa, A., Kraemer-Mbula, E., Rizk, N., Rutenberg, I. and De Beer, J., 2020. Artificial intelligence (AI) deployments in Africa: benefits, challenges and policy dimensions. *The African Journal of Information and Communication*, 26, pp. 1–28.

Gwagwa, A., 2020. Recommendations on the inclusion of sub-Saharan Africa in Global AI Ethics. *Research ICT Africa*. pp. 1–13.

Hawkins, A. (2018) 'Beijing's Big Brother Tech Needs African Faces', *Foreign Policy,* 24 July. Available at: https://foreignpolicy.com/2018/07/24/beijings-big-brother-tech-needs-african-faces/ (Accessed: 11 June 2021).

HDI. (2021) *China is Ready to Be come a Technological Superpower*. Available at: https://www.hdi.global/infocenter/insights/2021/china-technological-superpower/ (Accessed 11 June 2021).

Heckman, C. (2020) 'AI can now read emotions – should it?', *The Conversation*, 8 January. Available at: https://theconversation.com/ai-can-now-read-emotions-should-it-128988 (Accessed: 11 June 2021).

Heilweil, R. (2020) 'Big tech companies back away from selling facial recognition to police. That's Progress', *Vox,* 10 June. Available at: https://www.vox.com/recode/2020/6/10/21287194/amazon-microsoft-ibm-facial-recognition-moratorium-police (Accessed: 11 June 2021).

Hollanek, T., 2020. AI transparency: A matter of reconciling design with critique. *AI & SOCIETY*, pp. 1–9.

Oxford Insights. (2019). 'Government Artificial Intelligence Readiness Index 2019'. Available at: https://www.oxfordinsights.com/ai-readiness2019 (Accessed: 11 June 2021).

ITU. (2021) *Measuring Digital Development: Facts and Figures 2020*. Available at: https://www.itu.int/en/ITU-D/Statistics/Pages/facts/default.aspx (Accessed: 9 June 2021).

Jili, B. (2020). Chinese Surveillance Tools in Africa. Available at: https://cld.web.ox.ac.uk/files/finaljilipdf (Accessed: 11 June 2021).

Jo, E.S. and Gebru, T., 2020, January. Lessons from archives: Strategies for collecting sociocultural data in machine learning. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 306–316).

Killander, M. and Ilori, T. (2020) 'Internet shutdowns in Africa threaten democracy and development', *The Conversation,* 26 July. Available at: https://theconversation.com/internet-shutdowns-in-africa-threaten-democracy-and-development-142868 (Accessed: 11 June 2021).

Kohli, N., Barreto, R. and Kroll, J.A., 2018, February. Translation tutorial: a shared lexicon for research and practice in human-centered software systems. In the *1st Conference on Fairness, Accountability, and Transparency*. New York, NY, USA (Vol. 7).

Liu, X., Faes, L., Kale, A.U., Wagner, S.K., Fu, D.J., Bruynseels, A., Mahendiran, T., Moraes, G., Shamdas, M., Kern, C. and Ledsam, J.R., 2019. A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis. *The Lancet Digital Health, 1(6)*, pp.e271–e297.

Madden P. and Kanos D., (2021) *Figures of the week: Digital skills and the future of work in Africa*. Available at: https://www.brookings.edu/blog/africa-in-focus/2020/07/22/figures-of-the-week-digital-skills-and-the-future-of-work-in-africa/ (Accessed: 9 June 2021).

Makerere University. (2021) *DeepMind Supports Master's Scholarships to Study AI at Makerere University*. Available at: https://www.mak.ac.ug/slide/deepmind-supports-master%E2%80%99s-scholarships-study-ai-mak (Accessed: 11 June 2021).

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K. and Galstyan, A., 2021. A survey on bias and fairness in machine learning. *ACM Computing Surveys (CSUR), 54(6)*, pp. 1–35.

Microsoft. (2021) 'Microsoft collaborates with the Nigerian government to accelerate digital transformation in the country', *Microsoft News Center,* 03 May. Available at: https://news.microsoft.com/en-xm/2021/05/03/microsoft-collaborates-with-the-nigerian-government-to-accelerate-digital-transformation-in-the-country/ (Accessed: 9 June 2021).

MMC. (2019). The State of AI Divergence. Available at: https://mmc.vc/wp-content/uploads/2019/02/The-State-of-AI-2019-Divergence.pdf (Accessed: 10 June 2021)

Moosajee, N. (2021) 'Fix AI's racist, sexist bias', *The Mail & Guardian*, 14 March. Available at: https://mg.co.za/article/2019-03-14-fix-ais-racist-sexist-bias/ (Accessed: 11 June 2021).

Mozur, P., Kessel, J.M., and Chan, M. (2019). 'Made in China, exported to the world: the surveillance state', *The New York Times,* 24 April. Available at: https://www.nytimes.com/2019/04/24/technology/ecuador-surveillance-cameras-police-government.html (Accessed: 11 June 2021).

Mudongo, O., 2021. Africa's Expansion of AI Surveillance-Regional Gaps and Key Trends. *Research ICT Africa*. pp. 1–6.

Nantulya, P., 2018. Grand strategy and China's soft power push in Africa. Africa Center for Strategic Studies, pp. 1–3.

Ndiomewese, I. (2018) 'This Is Nigeria's First Ever Artificial Intelligence Hub', *Techpoint Africa*, 11 June. Available at: https://techpoint.africa/2018/06/11/nigerias-first-ever-artificial-intelligence-hub/ (Accessed: 11 June 2021).

Neri, E., Coppola, F., Miele, V., Bibbolino, C. and Grassi, R., 2020. Artificial intelligence: Who is responsible for the diagnosis?. *La Radiologia Medica, 125(6)*, pp. 517–521.

Nyabola, N. (2016) 'Facebook's Free Basics Is an African Dictator's Dream', *Foreign Policy*, 27 October. Available at: https://foreignpolicy.com/2016/10/27/facebooks-plan-to-wire-africa-is-a-dictators-dream-come-true-free-basics-internet/ (Accessed: 10 June 2021).

Olander, E. (2019) 'China And The Rise Of AI Surveillance Technology In Africa', *The China Africa Project,* 19 September. Available at: https://chinaafricaproject.com/analysis/china-and-the-rise-of-ai-surveillance-technology-in-africa/ (Accessed: 10 June 2021).

Parkinson, J., Bariyo N., and Chin J. (2019) 'Huawei Technicians Helped African governments spy on political opponents', *The Wall Street Journal*, 15 August. Available at: https://www.wsj.com/articles/huawei-technicians-helped-african-governments-spy-on-political-opponents-11565793017 (Accessed: 11 June 2021).

Perkowitz, S., 2021. The Bias in the Machine: Facial Recognition Technology and Racial Disparities. *MIT Case Studies in Social and Ethical Responsibilities of Computing*.

Polyakova, A. and Meserole, C., 2019. Exporting digital authoritarianism: The Russian and Chinese models. *Policy Brief, Democracy and Disorder Series* (Washington, DC: Brookings, 2019), pp. 1–22.

Prasad, R., 2018. Ascendant India, digital India: how net neutrality advocates defeated Facebook's Free Basics. *Media, Culture & Society, 40(3)*, pp. 415–431.

Raji, I.D., Smart, A., White, R.N., Mitchell, M., Gebru, T., Hutchinson, B., Smith-Loud, J., Theron, D. and Barnes, P., 2020a, January. Closing the AI accountability gap: defining an end-to-end framework for internal algorithmic auditing. In *Proceedings of the 2020a Conference on Fairness, Accountability, and Transparency* (pp. 33–44).

Raji, I.D., Gebru, T., Mitchell, M., Buolamwini, J., Lee, J. and Denton, E., 2020b, February. Saving face: Investigating the ethical concerns of facial recognition auditing. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society* (pp. 145–151).

Rakova, B., Yang, J., Cramer, H. and Chowdhury, R., 2021. Where responsible AI meets reality: Practitioner perspectives on enablers for shifting organizational practices. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1), pp. 1–23.

Roselli, D., Matthews, J. and Talagala, N., 2019, May. Managing bias in AI. In *Companion Proceedings of The 2019 World Wide Web Conference* (pp. 539–544).

Seutloali, G.M., 2015. Own-race bias in facial recognition amongst black, coloured and white participants. *PhD diss., University of Cape Town.*

Sharma, I., 2020. China's Neocolonialism in the Political Economy of AI Surveillance. *Cornell International Affairs Review, 13(2)*, pp. 94–154. https://doi.org/10.37513/ciar.v13i2.554

Shepherd, C. and Qiu, S. 2017. China's Xi lays out vision for 'new era' led by 'still stronger' Communist Party. Available at: https://www.reuters.com/article/us-china-congress-idUSKBN1CM35L

Maeve Shearlaw. (2016) 'Facebook lures Africa with free internet—but what is the hidden cost?', *The Guardian*, 01 August. Available at: https://www.theguardian.com/world/2016/aug/01/facebook-free-basics-internet-africa-mark-zuckerberg (Accessed: 10 June 2021).

Silberg, J. and Manyika, J., (2019) *Tackling bias in Artificial Intelligence (and in Humans*. Available at: https://www.mckinsey.com/featured-insights/artificial-intelligence/tackling-bias-in-artificial-intelligence-and-in-humans (Accessed 11 June 2021).

Teller, A. (2021) 'Loon's final flight', *Medium*, 21 January'. Available at: https://blog.x.company/loons-final-flight-e9d699123a96 (Accessed: 10 June 2021).

Tilouine, J. and Kadiri, G. (2018) 'A Addis-Abeba, le siège de l'Union africaine espionné par Pékin', *Le Monde.fr, 26 January*. Available at: https://www.lemonde.fr/afrique/article/2018/01/26/a-addis-abeba-le-siege-de-l-union-africaine-espionne-par-les-chinois_5247521_3212.html (Accessed: 11 June 2021).

Wareham, C.S., 2021. Artificial intelligence and African conceptions of personhood. *Ethics and Information Technology, 23(2)*, pp. 127–136.

Wojcik, S. and Remy, E., (2019) 'The Challenges of Using Machine Learning to Identify Gender in Images', *Pew Research Center,* 5 September. Available at: https://www.pewresearch.org/internet/2019/09/05/the-challenges-of-using-machine-learning-to-identify-gender-in-images/ (Accessed: 11 June 2021).

Woodhams, S. 2020. China, Africa, and the Private Surveillance Industry. *Georgetown Journal of International Affairs*, 21, pp. 158–165.

World Bank. (2019a) *TICAD Seminar Series: DE4A initiative*. Available at: https://pubdocs.worldbank.org/en/312571561424182864/062519-digital-economy-from-africa-initiative-Tim-Kelly.pdf (Accessed: 9 June 2021).

World Bank. (2019b) *Achieving Broadband Access for All in Africa Comes with a $100 Billion Price Tag*. Available at: https://www.worldbank.org/en/news/press-release/2019b/10/17/achieving-broadband-access-for-all-in-africa-comes-with-a-100-billion-price-tag (Accessed: 9 June 2021).

World Bank. (2020) *Digital Skills for all African Students: What Will it Take?* 28 Feb. Available at: https://www.worldbank.org/en/news/feature/2020/04/14/digital-skills-for-all-african-students-what-will-it-take (Accessed: 9 June 2021).

World Bank. (2021). *Digital Economy for Africa Initiative*. Available at: https://www.worldbank.org/en/programs/all-africa-digital-transformation (Accessed: 9 June 2021).

X, the moonshot factory. (2017) *Loon, Expanding Internet Connectivity with Stratospheric Balloons*. Available at: https://loon.com/ (Accessed: 10 June 2021).

Zeiger, H. (2020) 'China's Eyes Are Watching Africa Closely.' *Mind Matters News* Available at: https://mindmatters.ai/2020/11/chinas-eyes-are-watching-africa-closely/ (Accessed: 09 May 2021).

Zeng, Y., Lu, E., Sun, Y. and Tian, R., 2019. Responsible facial recognition and beyond. *arXiv preprint* arXiv:1909.12935.