RESPONSIBLE ARTIFICIAL INTELLIGENCE FOR AFRICA'S AGRICULTURE AND FOOD SYSTEMS CHALLENGES AND OPPORTUNITIES

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Responsible Artificial Intelligence for Africa's Agriculture and Food Systems: Challenges and Opportunities

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The African Technology Policy Studies Network (ATPS) is a transdisciplinary network of researchers, policymakers, private sector actors and the civil society promoting the generation, dissemination, use and mastery of Science, Technology and Innovations (STI) for African development, environmental sustainability and global inclusion. In collaboration with like-minded institutions, ATPS provides platforms for regional and international research and knowledge sharing in order to build Africa's capabilities in STI policy research, policymaking and implementation for sustainable development.

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About the Participating Organizations

The African Technology Policy Studies Network (ATPS):
The ATPS is a trans-disciplinary network of researchers, policymakers, private sector actors and civil society actors that promote the generation, dissemination, use and mastery of STI for African development, environmental sustainability and global inclusion. ATPS has over 5,000 network members and 3,000 stakeholders in over 51 countries in 5 continents with institutional partnerships worldwide. In the 1980s, two distinct networks emerged in Africa: Eastern and Southern Africa Technology Policy Studies and Western Africa Technology Policy Studies.

In 1994, ATPS was established as a secretariat within the East and Southern Africa Regional Office of the IDRC. In 2000, ATPS became an autonomous international organization with diplomatic status in Kenya and working on trans-disciplinary STI themes for African development. Whilst retaining the STI focus, ATPS has moved towards a “knowledge for development” network for Africa. Programs are implemented through members in national chapters established in 30 countries (27 in Africa and 3 Diaspora chapters in Australia, USA and UK). In collaboration with like-minded institutions, ATPS provides platforms for regional and international research and knowledge sharing to build Africa’s capabilities in STI policy research, policymaking and implementation for sustainable development.

The ATPS Mission is to improve the quality of STI systems research, policy and practice by strengthening the capacity for STI knowledge generation, dissemination, and use for sustainable development in Africa. The overall objective is to build Africa's science, technology, and innovation capabilities for sustainable development and global inclusion. The ATPS Phase VIII Strategic Plan, 2017-2022 identifies four thematic priority areas of intervention namely: Agriculture, food and nutrition; Energy; Climate change and environment; and Health innovations. The Strategic Plan also identifies five cross-cutting programmatic priority areas namely: STI policy research, policymaking and advocacy; Training, sensitization and capacity building; Youth and gender empowerment; Knowledge brokerage, management and commercialization; and Intra-Africa and global collaboration. These priority areas align perfectly to deliver on the overall and specific objectives of the AI4AFS.

International Centre of Insect Physiology and Ecology (icipe): Established in 1970, icipe is a Pan-African research-for-development inter-governmental organization. With operations in 41 African countries, the Centre has more than 500 staff based in Kenya, Ethiopia and Uganda, and more than 300 partners globally, including 43 African universities. Icipe is a Stockholm Convention Regional Centre aiming to reduce the use of persistent organic pollutants for pest management, a World Organization for Animal Health Collaborating Centre for Bee Health in Africa, a FAO Reference Centre for Vectors and Vector-borne Animal Diseases, and a WHO-AFRO partner for Management of Vectors.

As a centre of excellence, icipe is committed to building the capacity of people and institutions to respond to the development needs of Africa. It has a proud tradition and an excellent reputation as an incubator of some of Africa's best young scientists, with 150-180 graduate students trained annually. The recently established icipe's Data Management, Modelling and Geo-information (DMMG) unit is mandated to advance application of responsible artificial intelligence in Plant Health, Animal Health, Human Health and Environmental Health, the 4Hs of icipe's research focus. The unit is responsible for use of advanced methods and analytics including machine learning (ML), artificial intelligence (AI), design thinking, system thinking and system dynamics and computer vision algorithms to exploit and interpret 'big data' to develop geospatial cloud-based tools and mobile apps that can be operationally utilized for 'real-time' insect, plant and environmental health indicators surveillance, monitoring and forecasting. Moreover, the unit team works on the use of hyper-spatial unmanned aerial vehicles and satellite-based high definition videos and altimetric information that can improve the understanding of various plant, animal, human and environmental health issues.

Modelling activities in the unit include the application of advanced mathematical, physical and statistical methods to data on pests/diseases in animals, ecosystems, plants, and humans. Emphasis is placed on research activities aimed at developing, applying and exploring new computational techniques for decision support in the context of agricultural systems, disease vectors control, environmental assessment, integrated pest management (IPM) implementation practices and interventions, and climate change and variability impact assessments.

Kumasi Hive:

Kumasi Hive is a tech and innovation hub for rapid prototyping of ideas, budding local innovations, impact start-up support and the promotion of youth entrepreneurship as a way of addressing critical social, economic, and developmental challenges. Kumasi Hive focuses on building the capacity of young people in the technology and business spaces while creating sustainable innovations that solve local and global challenges. It exists to support entrepreneurs and innovators of all types, particularly to encourage social impact businesses to develop innovative physical products and processing methods.

Abstract

Africa's population is expected to reach about 2.6 billion by 2050. This will require an increase in agricultural and food production by up to 70% to meet the need of the growing population, a serious challenge for the agriculture and food systems. Such requirement, in a context of resource scarcity, climate change, COVID-19 pandemic, global conflicts, and very harsh socioeconomic conjecture, is difficult to attain unless we embrace emerging technologies and innovations such as artificial intelligence to leapfrog the transformations required in the sector.

This Working Paper aims to showcase the challenges and opportunities in the responsible development, deployment, and scaling of home-grown artificial intelligence research and innovations in Africa to tackle pressing challenges in agriculture and food systems. Key challenges were identified namely; lack of data for implementation, inadequate number of skilled researchers, unavailability of focused policies and institutional support, gender gaps, environmental concerns embedded in carbon footprint information, and technological gaps. Opportunities identified include; increased gender inclusion in STEM, responsible carbon footprint reporting with enhanced green practice, increased new jobs in the AI workforce, increased research opportunities for donor funding, the formation of strong synergy between stakeholders, and innovations to improve agriculture and food production.

Other opportunities include: setting up of artificial intelligence innovation research network for agriculture and food systems; managing the innovation research network; and fostering collaborations, knowledge exchange, and valorization within the network and beyond. It is expected that through these interventions, responsible and homegrown artificial intelligence research and innovations will be developed, deployed, and scaled to tackle pressing challenges in agriculture and food systems in Africa.

The paper identified critical guiding documents from the International Technology Law Association (ITECHLAW) and the European Union Commission as a reference to Artificial Intelligence application in Africa in general and specifically AI application in agriculture and food systems. If responsibly applied, AI in agriculture and food systems is a panacea for Africa's development. Hence core principles of responsible AI use must be mainstreamed to ensure human-centered design, privacy, and intellectual property compliance, with ethics and robustness.

1. Introduction

After decades of lethargy, most of Africa is experiencing rapid economic transformation. Half of the world's ten fastest-growing economies are in sub-Saharan Africa (Kearney, 2014). Africa's dynamism has spawned efforts to identify the 'megatrends' driving the region's economic growth and anticipate the future opportunities and challenges associated with these trends. Among the most frequently cited trends are; the rise of the African middle class (African Development Bank, [AfDB], 2012), rapid urbanization and consequent shifts in food demand and downstream modernization of agriculture and food systems (Tschirley et. al., 2015), a rapid shift in the labour force from farming to non-farm jobs (Fine et. al., 2012), and rising global interest in African farmland (Schoneveld, 2014).

Agriculture remains the bedrock of sustainability of African economies (Kekane, 2013) where it plays a key part in long-term economic growth and structural transformation (Syrquin, 1988), though, may vary by country (Dekle and Vandenbroucke, 2012). In the past, agricultural activities were limited to food crop production (Fan et. al., 2012), but in the last few decades, it has evolved to encompass the food systems comprising the entire range of actors and their interlinked value-adding activities involved in the production, aggregation, processing, distribution, consumption, and disposal of food products that originate from agriculture, forestry or fisheries, and parts of the broader economic, societal and natural environments in which they are embedded (Food and Agriculture Organization [FAO], 2018). Agriculture and food systems (AFS) provide the basic source of livelihood, improving Gross Domestic Product

(GDP) (Oyakhilomen and Zibah, 2014), a source of national trade, reducing unemployment, providing raw materials for production in other industries, and overall development of economies (Awokuse, 2009). That notwithstanding, AFS still fails to supply the required food needs of the developing regions, especially in Africa. According to FAO et. al. (2020), food security is not improving in Africa.

While about 795 million people are undernourished globally, including 90 million children under the age of five (FAO, International Fund for Agricultural Development [IFAD] and World Food Programme [WFP], 2015), the vast majority of them totalling 780 million people live in the developing regions, notably in Africa and Asia (United Nations Conference on Trade and Development [UNCTAD], 2017). In particular, sub-Saharan Africa (SSA) is worse, with almost 25% of the population undernourished (FAO et. al., 2015).

The inability of African countries especially SSA to feed their population poses greater challenges to their development. The agricultural sector in the region is characterized by over-reliance on primary products, low fertility soils, minimal use of external farm inputs, environmental degradation, significant pre, and post-harvest losses, low yields, minimal value addition, and inadequate food storage and preservation that result in significant commodity price fluctuations.

The COVID-19 pandemic and unprecedented desert locust outbreaks in Eastern Africa have exacerbated economic prospects in ways no one could have anticipated, and the situation may only worsen if we do not act urgently and take unprecedented measures (FAO et. al., 2020). These challenges occur mainly because of poorly developed and non-adoption of good mixes of low to high technologies by small-scale farmers who form the bulk of the farming population in Africa (Ozor and Urama, 2013). With the current geometric rise in Africa's population estimated to reach about 2.6 billion by 2050 and a growth rate of more than 2.5% p.a. (Population of Africa, 2019), it becomes imperative that agriculture and food systems (AFS) are reviewed to embrace innovative approaches for sustaining and improving the system from production to utilization. One of the most promising ways for achieving this target is through science, technology, and innovation (STI) (Ozor and Urama, 2013; UNCTAD, 2017).

STI is recognized as a means for achieving the sustainable development goal (SDG) 2 (End hunger). Artificial Intelligence (AI), which is the capacity of a machine to perform cognitive functions associated with human minds, such as perceiving, reasoning, learning, interacting with the environment, solving problems, and even exercising creativity (Manyika et. al., 2017), stands out as one of the emerging technologies with a great potential to transform the AFS and ensure that all aspects of food security including food availability, access, utilization, and stability are achieved even for small-scale farm enterprises in Africa.

The introduction of AI for AFS is enabled by other technological advances such as big data, robotics, machine learning (ML), Internet of Things (IoT), availability of affordable sensors and cameras, drone technology, and even wide-scale internet coverage of geographically dispersed fields (Eli-Chukwu, 2019). Despite the growth of movements applying ML, IoT, and AI among other tools to solve the AFS challenges, there remains the need to identify how these tools may best benefit Africa under its peculiar circumstances.

1.1 Justification for responsible AI in Africa's agriculture and food systems

Globally, agriculture and food production will continue to be affected by two driving forces namely; the increase in population, particularly in Africa, and; climate change, which will heighten the challenge of feeding more people.

To overcome these two challenges, Africa must pursue the path of a sustainable food security trajectory, which involves a mix of different approaches with the application of STI being paramount (UNCTAD, 2017). Agriculture in Africa has a massive social and economic footprint. More than 60% of the population of SSA are smallholder farmers, and about 23% of SSA's GDP comes from agriculture (Goedde et. al., 2019). Yet, Africa's full agricultural potential to feed itself and industrialize the sector remains untapped.

According to Goedde et. al., (2019), Africa could produce two to three times more cereals and grains, which would add 20% more cereals and grains to the current worldwide 2.6 billion tons of output. Similar increases could be seen in the production of horticulture crops and livestock. Still, these remain unrealized because the agriculture and food sector have not been digitized amidst other social, economic, and political constraints. Regarding supply chain issues, the continent's retail modernization is still in the early stages of development, and more than 90% of African commerce occurs in informal markets or at the micro-retail level (Nieuwoudt, 2019).

The overarching agricultural challenge for science in Africa is how the persisting low productivity in the farming systems can be transformed. Among the main challenges are a lack of coherent and conducive policies; poor incentives; poor access to input and output markets; predominant rain-fed agriculture; inadequate agricultural research and development (R&D) spending; heavily degraded and depleted soils; problematic land tenure systems; poor mechanization; pests, diseases, and weeds; and climate change (Forum for Agricultural Research in Africa [FARA], 2014).

Agriculture is the backbone of Africa's economy and accounts for the majority of livelihoods across the continent, yet the sector is underdeveloped. The global population is expected to reach more than 9 billion by 2050, which will require an increase in agricultural production by 70% to fulfil the demand. Only about 10% of this increased production may come from unused lands and the rest should be fulfilled by current production intensification and STI (Eli-Chukwu, 2019 and UNCTAD, 2017). Over 870 million people suffer from chronic undernourishment, 27% of which are in Africa alone (World Hunger Education Service, 2013).

A growing global population, particularly in Africa, exacerbates this challenge. In this context, the use of the latest technological solutions to make farming more efficient remains a great necessity. It, therefore, follows that the solutions to these key challenges are needed quickly and answers can be obtained through the application of STI which AI can have a profound impact on the future of AFS in Africa (UNCTAD, 2017).

1.2 Purpose and Objectives of the Research

The overall purpose of the study is to examine the place of responsible artificial intelligence (AI) in agriculture and food systems (AFS) while identifying the accompanying challenges and opportunities in its development, deployment, and scaling in Africa. Most specifically, the research study aims to:

i) Review the theoretical underpinnings and principles around responsible AI
ii) Examine the rationale for the application of responsible AI in AFS;
iii) Identify the specific areas in AFS where AI can be applied to boost food and nutrition security in Africa;
iv) Examine the challenges for effective development, deployment, and scaling of AI in African AFS;
v) Examine the opportunities that AI presents in ensuring adequate food and nutrition security in Africa; and
vi) Proffer recommendations for effective development, deployment, and scaling of responsible AI in AFS in Africa.

2. Methodology

This review focuses on the challenges and opportunities in the responsible development, deployment, and use of AI in Africa's agriculture and foods system. Africa's continent is home to over 137 billion people, with a Gross Domestic Product (GDP) of 270 billion as of 2021 (AFDB, 2021).

The data collected was mainly qualitative and partly quantitative. The sources were from 100 relevant literature published between 1996 and 2022; information was analysed according to importance concerning the study area and subject.

Other sources of data included AI webinars like the 1st Artificial Intelligence for Development (AI4D) innovation Hubs learning forum organized by the International Development Research Centre (IDRC) and the Swedish International Development Agency (Sida) on 28th January 2022 and Advancing Data Justice in AI organized by Centre for Intellectual Property and Information Technology Law (CIPIT) workshop on February 23rd 2022. The information aggregated is shown in the succeeding sections.

3. Theoretical underpinnings and principles around responsible Artificial Intelligence

3.1 Theoretical background to taking responsibility in AI4AFS

Responsible AI implementation in AFS is embedded in the design of products, services, and the attitude of designers and funders. The stakeholders in responsible AI in Agriculture and food systems include AI designers and AI developers, data scientists, procurement officers or specialists, front-end staff that will use or works with the AI system, legal/compliance officers, and management.

3.1.1 What is Artificial Intelligence

Artificial Intelligence (AI), which is the capacity of a machine to perform cognitive functions associated with human minds, such as perceiving, reasoning, learning, interacting with the environment, solving problems, and even exercising creativity (Manyika et. al., 2017), stands out as one of the emerging technologies with a great potential to transform the AFS and ensure that all aspects of food security including food availability, access, utilization, and stability are achieved even for small-scale farm enterprises in Africa.

3.1.2 What is responsible Artificial Intelligence

Responsible AI is the practice of designing, developing, and deploying

AI that is lawful, ethical, robust, societal, and environmentally friendly, with good intentions to empower people. Responsible AI (RAI) is the only way to mitigate AI risks.

3.1.3 Responsible Design

Responsible design involves ensuring that the development processes during the project consider the ethical and societal implications of AI as it integrates and replaces traditional systems and social structures (Zhu et al., 2022). It means integrating ethical reasoning ability as part of the behaviour of the artificial autonomous systems.

It also implies that the behaviour of the systems must be in tandem with what is or it is replacing to avoid any user conflicts which involve reorientation.

3.1.4 Responsibility of the Designer/Grantee

This involves a measure of research integrity of the researcher and manufacturers, certifications, and mechanisms. The designer ensures all the ethical considerations in line with the responsible AI core principles are diligently adhered to and followed. The designer understands that he/she is accountable for the designs.

3.1.5 Responsibility of the AI Stakeholders

The stakeholders should be responsible for ensuring the projects implemented by the grantees follow all the laid down guidelines and principles of responsible AI. These involve:

i) ***Innovating Responsibly:*** Drive responsible AI innovations in AFS by putting the core principles of responsible AI into practice by taking a people-centered approach to AI research, development, and deployment. To achieve this, we embrace diverse perspectives, continuous learning, and agile responsiveness as AI4AFS technology evolves (Zhu et al., 2022).

ii) ***Empowering others:*** there is a need to cultivate a responsible AI-ready culture throughout their research and put principles into place from implementation to governance with practices, tools, and technologies built on multidisciplinary research, shared learning, and leading innovation. These will be achieved through capacity-building workshops on responsible AI in agriculture and food systems (Zhu et al., 2022).

iii) ***Fostering positive impact:*** There should be a commitment to ensuring AI technology has a lasting positive impact on everyone by helping to shape public policy, contributing to industry working groups, and empowering those working to address society's most significant challenges.

3.2 The principles of responsible AI

The core principles guiding the implementation of a responsible AI4AFS according to ITECHLAW (2021) on the global responsible AI policy framework are shown in figure 1. Understanding these core principles is central to the ethical success of this intended AI project. These core principles are elaborated on in the preceding paragraphs.

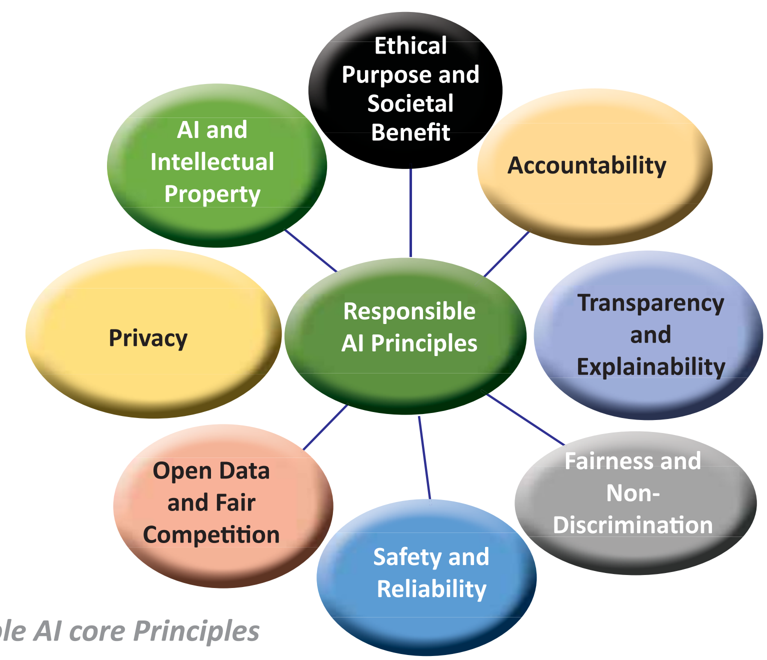


Fig 1: Responsible AI core Principles

3.2.1 Ethical Purpose and Societal Benefit

Establishments that develop, deploy or use AI systems and any national laws that control such use should require the purposes of such application to be identified and ensure that such purposes are consistent with the overall moral purposes of beneficence and non-maleficence, as well as the other principles of the Policy Framework for Responsible AI (Powling & Hammer, 2019). It implies that organizations/individuals that develop, deploy, or use AI systems should do so in a manner compatible with human agency and respect for fundamental human rights (including freedom from discrimination) (Dormehi, 2019).

Any organization/ individuals that develop, deploy, or use AI systems should monitor the implementation of such AI systems and act to mitigate against consequences of such AI systems (whether intended or unintended) that are inconsistent with the ethical purposes of beneficence and non-maleficence, as well as the other principles for Responsible AI set out in the country or regional guiding policies.

Finally, all that develop, deploy or use AI systems should assess the social, political, and environmental implications of such development, deployment, and use in the context of a structured Responsible AI Impact Assessment that evaluates the risk of harm and, as the case may be, proposes mitigation strategies in relation to such risks (Feldstein, 2019).

3.2.2 Accountability

In all instances, humans should remain accountable for the acts and omissions of AI systems. All organizations or individuals that develop, deploy, or use AI systems shall designate an individual or individuals who are accountable for the organization's compliance with those principles. The identity of the individual(s) designated by the organization to oversee the organization's compliance with the principles shall be made known upon request (Villaronga & Golia, 2019).

All organizations/ individuals that develop, deploy or use AI systems shall implement policies and practices to give effect to the principles of the Policy Framework for Responsible AI or other adopted principles (including analogous principles that may be developed for a specific industry), including:

i. establishing processes to determine whether, when, and how to implement a "Responsible AI Impact Assessment" process;
ii. establishing and implementing "Responsible AI by Design" principles;
iii. establishing procedures to receive and respond to complaints and inquiries;
iv. training staff and communicating to staff information about the organization's policies and practices; and
v. developing information to explain the organization's policies and procedures (Villaronga & Golia, 2019).

3.2.3 Transparency and Explainability

Organizations that develop, deploy or use AI systems and any national laws that regulate such use shall ensure that, to the extent reasonable given the circumstances and state of the art of the technology, such use is transparent and that the decision outcomes of the AI system are explainable.

Transparency is an obligation for organizations that use AI in decision-making processes to provide information regarding a) the fact that an organization is using an AI system in a decision-making process; b) the intended purpose(s) of the AI system and how the AI system will and can be used; (c) the types of data sets that are used by the AI system; and (d) meaningful information about the logic involved (Keller, 2020).

Explainability is an obligation for organizations that use AI in decision-making processes to provide accurate information in humanly understandable terms explaining how a decision/outcome was reached by an AI system (Metz, 2019). Transparency and Explainability aim to preserve the public's trust in AI systems and provide sufficient information to help ensure meaningful accountability of an AI system's developers, deployers, and users, and to demonstrate whether the decisions made by an AI system are fair and impartial.

The Transparency and Explainability principles support the Accountability principle, the Fairness and Non-Discrimination principle, the Safety and Reliability principle, and the Privacy, Lawful Use, and Consent principles. In areas of AI design, Organizations that develop AI systems should ensure that the system logic and architecture serve to facilitate transparency and explainability requirements. In so far as is reasonably practicable and considering the state of the art at the time, such systems should aim to be designed from the most fundamental level upwards to promote transparency and explainability by design. Where there is a choice between system architectures that are less or more opaque, the more transparent option should be preferred (Loi and Christen, 2019).

3.2.4 Fairness and Non-Discrimination

Decisions based on AI systems should be fair and non-discriminatory, judged against the same standards as decision-making processes conducted entirely by humans (European Commission, 2019). The use of AI systems by organizations that develop, deploy or use AI systems and Governments should not serve to exempt or attenuate the need for fairness, although it may mean refocussing applicable concepts, standards and rules to accommodate AI.
Users of AI systems and persons subject to their decisions must have an effective way to seek remedy in discriminatory or unfair situations generated by biased or erroneous AI systems, whether used by

organizations that develop, deploy or use AI systems or governments, and to obtain redress for any harm (China Ministry of Science and Technology, 2019).

AI systems can perpetuate and exacerbate bias and have a broad social and economic impact on society. Addressing fairness in AI use requires a holistic approach. In particular, it requires:

i. the close engagement of technical experts from AI-related fields with statisticians and researchers from the social sciences; and

ii. a combined engagement between governments, organizations that develop, deploy or use AI systems, and the public at large.

3.2.5 Safety and Reliability

Organizations that develop, deploy, or use AI systems and any national laws regulating such use shall adopt design regimes and standards ensuring high safety and reliability of AI systems while limiting the exposure of developers and deployers, on the other hand.

All developing, deploying, or using AI systems should recall that ethical and moral principles are not globally uniform but may be impacted by geographical, religious, or social considerations and traditions. To be accepted, AI systems might have to be adjustable in order to meet the local standards in which they will be used. Consider whether all possible occurrences should be pre-decided in a way to ensure the consistent behaviour of the AI system, the impact of this on the aggregation of consequences, and the moral appropriateness of "weighing the unweighable" such as life vs. life (Gardner et al., 2021).

Regulating agencies should be required, and organizations should test AI systems thoroughly to ensure that they reliably adhere, in operation, to the underpinning ethical and moral principles and have been trained with data that are curated and are as ‘error-free’ as practicable, given the circumstances. All are encouraged to adjust regulatory regimes and/or promote industry self-regulatory regimes to allow market-entry of AI systems to reasonably reflect the positive exposure that may result from the public operation of such AI systems (Buyers and Barty, 2021). Special regimes for intermediary and limited admissions to enable testing and refining of the AI system’s operation can help expedite the completion of the AI system and improve its safety and reliability (Gardner et al., 2021).

In order to ensure and maintain public trust in absolute human control, governments should consider implementing rules that ensure comprehensive and transparent investigation of such adverse and unanticipated outcomes of AI systems that have occurred through their usage, in particular, if these outcomes have lethal or dangerous consequences for the humans using such systems.

3.2.6 Open Data and Fair Competition

Organizations that develop, deploy or use AI systems and any national laws that regulate such use shall promote (a) open access to datasets that could be used in the development of AI systems and (b) open-source frameworks and software for AI systems. AI systems must be developed and deployed on a “compliance by design” basis in relation to competition/antitrust law. Organizations that develop AI systems are normally entitled to commercialize such systems as they wish (European Commission, 2020).

However, governments should at the very least advocate accessibility through open source or other similar licensing arrangements to those innovative AI systems which may be of particular societal benefit or advance the “state of the art” in the field via, for example, targeted incentive schemes.

Organizations that elect not to release their AI systems as open-source software are encouraged nevertheless to license the System on a commercial basis. To the extent that an AI system can be sub-divided into various constituent parts with general utility and application in other AI use-cases, organizations that elect not to license the AI system as a whole (whether on an open source or commercial basis) are encouraged to license as many of such re-usable components as is possible.

3.2.7 Privacy

Organizations that develop, deploy or use AI systems and any national laws that regulate such use shall endeavour to ensure that AI systems are compliant with privacy norms and regulations, taking into account the unique characteristics of AI systems, and the evolution of standards on privacy. There is an inherent and developing conflict between the increasing use of AI systems to manage private data, especially personal data; and the increasing regulatory protection afforded internationally to personal and other private data (Powling & Hammer, 2019). Governments that regulate the privacy implications of AI systems should do so in a manner that acknowledges the specific characteristics of AI and that does not unduly stifle AI innovation.
Organizations that develop, deploy and use AI systems should analyse their current processes to identify whether they need to be updated or amended in any way to ensure that respect for privacy is a central consideration (Powling & Hammer, 2019).

AI systems create challenges specifically in relation to the practicalities of meeting requirements under several national legislative regimes, such as consent and anonymization of data. Accordingly, organizations that develop, deploy or use AI systems and any national laws regulating such use shall provide alternative lawful bases for the collection and processing of personal data by AI systems.

These organizations should consider implementing operational safeguards to protect privacy by designing principles tailored to the specific features of deployed AI systems (Feldstein, 2019).

Additionally, they should appoint an AI Ethics Officer, in a role similar to Data Protection Officers under the GDPR, but with a specific remit to consider the ethics and regulatory compliance of their use of AI. Although there are challenges from a privacy perspective from the use of AI, in turn, the advent of AI technologies could also be used to help organizations comply with privacy obligations (Feldstein, 2019).

3.2.8 AI and Intellectual Property

Organizations that develop, deploy or use AI systems should take necessary steps to protect the rights in the resulting works through appropriate and directed application of existing intellectual property rights laws. Governments should investigate how AI-authored works may be further protected without creating any new IP right at this stage. Organizations must therefore be allowed to protect rights in works resulting from the use of AI, whether AI-created works or AI-enabled works (WIPO, 2020).

3.3 European Union Perspective on Principles of Responsible AI

As a general guiding statement European Commission (European Commission, 2019); a trustworthy AI development, deployment, and use must be lawful (respecting all applicable laws and regulations), ethical (respecting ethical principles and values), and robust (both from a technical perspective while taking into consideration its social environment).

All applicants should fully understand the guiding principles of responsible or trustworthy AI development, deployment, and utilization as found out in a set of 7 essential requirements that AI systems should meet in order to be deemed trustworthy. A specific assessment list aims to help verify the application of each of the critical requirements according to European Commission (2019). Some of the key requirements or guiding principles are:

Human agency and oversight: AI systems should empower human beings, allowing them to make informed decisions and fostering their fundamental rights. At the same time, proper oversight mechanisms need to be ensured, which can be achieved through human-in-the-loop, human-on-the-loop, and human-in-command approaches.

Technical Robustness and safety: AI systems need to be resilient and secure. They need to be safe, ensuring a fallback plan in case something goes wrong, as well as being accurate, reliable, and reproducible. That is the only way to ensure unintentional harm is minimized and prevented.

Privacy and data governance: besides ensuring full respect for privacy and data protection, adequate data governance mechanisms must also be ensured, taking into account the quality and integrity of the data, and ensuring legitimized access to data.

Transparency: the data, system, and AI business models should be transparent. Traceability mechanisms can help achieve this. Moreover, AI systems and their decisions should be explained in a manner adapted to the stakeholder concerned. Humans need to be aware that they are interacting with an AI system, and must be informed of the system's capabilities and limitations.

Diversity, non-discrimination and fairness: Unfair bias must be avoided, as it could have multiple negative implications, from the marginalization of vulnerable groups to the exacerbation of prejudice and discrimination. To promote diversity, AI systems should be accessible to all, regardless of differences in physical and social abilities, and involve relevant stakeholders throughout their entire life cycle.

Societal and environmental well-being: AI systems should benefit all human beings, including future generations. It must hence be ensured that they are sustainable and environmentally friendly. Moreover, they should take into account the environment, including other living beings, and their social and societal impact should be carefully considered.

Accountability: Mechanisms should be put in place to ensure responsibility and accountability for AI systems and their outcomes (Buyers and Barty (2021). Auditability, which enables the assessment of algorithms, data, and design processes plays a key role therein, especially in critical applications. Moreover, adequate and accessible redress should be ensured.

4. Rationale for responsible AI in Africa's Agriculture and Food Systems

An essential goal of responsible AI is to reduce the risk that a minor change in an input's weight will drastically change the output of a machine learning model. The issue of responsible AI arises due to the autonomous nature of AI systems. There is need to adhere to a clear set of values that are core to successful AI implementation by delivering solutions with integrity, respecting individuals, and always being mindful of the social impact of products and services.

In reality, responsible AI will involve products and services that do not cause an end to the world or, in this case, limit or reduce agricultural and food systems growth, but stimulates a sustainable increase in the product while maintaining integrity, respect, and positive social impacts (Balagué, 2021). An example is the automatic agro-product sorting machine that uses high electromagnetic waves.

The autonomous system should cause no harm to the end-user, meet international standards, support gender ethics, and not cause any damage to the environment. Fairness and equity are mostly misunderstood. Responsible AI ensures justice and equity through safe practices, high awareness, the ability to replace, maintaining privacy principles without bias, and ensuring human dignity.

Some of the advantages of responsible AI in agricultural and food system research and development include the following:

a) It benefits the public good and minimizes unintended consequences, especially those infringing on individual rights and liberties.

b) Adopting a “responsible AI” framework is an urgent moral imperative due to rapid innovation across all sectors of society. There is a high risk of potential societal and individual harm because very few people truly understand the technology and because the technology may have such a significant impact on many.

c) Takes a holistic approach to development and execution at all levels, intentionally engaging with diverse stakeholders and acknowledging that industry and government stakeholders are looking for practical guideposts for responsible conduct.

d) It follows emerging global consensus and models around ethical AI best practices.

e) Places the notion of human “accountability” at the heart of the framework (making organizations that develop, deploy or use AI systems accountable for the harm caused by AI).

f) Rejects the notion of granting legal personality to AI systems.

g) Commits to avoid bias and discrimination through regularly tested and evaluated systems and practices and the inclusion of diverse stakeholders.

To be considered responsible, AI mandates the use of shared code repositories, approved model architectures, supported variables, and established bias testing methods to determine validity, which is part of an enterprise-wide development standard.

All AI system testing should be built at the grassroots level using resources and technology stability criteria for active machine learning models to ensure that AI programming works as intended. Promotes transparency and explainability of AI systems to promote humanity. Identifies and explains when and how operations involve humans or AI-driven nonhumans.

Artificial intelligence is complex, high risk, and quickly embedding itself into our everyday lives, often without people realizing it. No universal guidelines for responsible AI exist yet, hence the need for responsibility.

The question is, who takes responsibility when something goes wrong? Therefore, responsible AI is a governance framework that documents how a specific organization addresses the challenges around AI from both an ethical and legal point of view (Begishev & Khisamova, 2021). Resolving ambiguity about where responsibility lies if something goes wrong is essential for responsible AI initiatives.

Artificial Intelligence is beneficial to human endeavours but can be harmfully used if not checked. Hence the need for organizations, individuals, and society to take responsibility (Paliwal et al., 2022).

These are six fundamental reasons why AI used in our lives must be responsible:

a) Because AI is being embedded into nearly every profession and industry worldwide in ways that will change how we as humans and organizations connect, work, play, and learn—in other words, our daily experiences.

b) Technology has a significant capacity to disrupt and distort, potentially benefiting and/or harming humankind and the rights, protections, and values we all currently enjoy.

c) AI is complex and understood by few people, creating a serious imbalance of comprehension and inadequate permission-giving by ordinary people whose lives are often unknowingly being changed.

d) AI is already being explored and applied for malicious purposes that threaten our safety, security, and human rights.

e) The risks of bias, discrimination, deception and privacy infringement are high due in part to inadequate engagement by diverse stakeholders in the development, application, and accountability of AI systems and products.

No universal standards of responsible AI exist, so many AI providers and users are not operating within a best-practices framework that holds themselves accountable for the reliance, fairness, and impact of this transformative technology. Responsible AI involves other aspects which are gender inclusion and support and carbon footprint tracking which ensure the environmental friendliness of all activities. The next subsection will examine the rationale for responsible gender support and carbon footprint report.

4.1 Rationale for Gender Support and Inclusion

4.1.1 Overview of Gender Support and Inclusion

Gender refers to the socially constructed characteristics of women, men, girls, and boys. This includes norms, behaviours, and roles associated with being a woman, man, girl, or boy, and relationships with each other. As a social construct, gender varies from society to society and can change over time. Gender refers to psychological, social, and cultural factors that shape attitudes, behaviours, stereotypes, technologies, and knowledge. Gender norms refer to spoken and unspoken rules in the family, workplace, institution, or global culture that influence individuals (Prates et al., 2019).

Gender identity refers to how individuals and groups perceive and present themselves within specific cultures. Gender relations refer to power relations between individuals with different gender roles and identities (Nomura, 2017). Gender-specific reporting is still limited in a range of scientific disciplines (Scanes et al., 2021). In most science, and engineering output, certain norms are gender-biased (Potluri et al., 2017). A review of experimental ocean acidification studies in marine science showed that only 3.9% of studies statistically assessed sex-based differences (Buolamwini and Gebru, 2018). In comparison, only 10.5% of studies accounted for possible sex effects by assessing females and males independently (Khramtsova et al., 2019).

Analysing experimental results by sex and gender is critical for improving accuracy and avoiding misinterpretation of data. Scientists have erroneously assumed that females should be excluded from experiments because of the variable nature of the data caused by the reproductive cycle (Beery 2018). Research has shown that males exhibit equal or more significant variability than females for specific traits owing to fluctuations in testosterone levels and other factors, such as animal group caging (Li et al., 2017). An often neglected but crucial component of engineering is understanding the broader social impacts of the technology being developed and ensuring that the technology enhances social equity and equality by benefitting diverse populations (Li et al., 2017).

Human bias and stereotypes can be perpetuated and even amplified when researchers fail to consider how human preferences and assumptions may consciously or unconsciously be built into science or technology. Gender norms, ethnicity, and other biological and social factors are shaped by science and technology in a robust cultural feedback loop (Cripps et al., 2016). Hence, gender inclusion is a concept that transcends mere equality. It is the notion that all services, opportunities, and establishments are open to all people and that male and female stereotypes do not define societal roles and expectations.

Gender inclusion and support aid in the removal of barriers to technology adoption and use. Since most technology beneficiaries are women, gender inclusion and support will enhance participation, thus removing any perceived bias, and increasing the willingness to produce, adopt, and disseminate technology.

Current suites show that technology intervention most times displaces women, thus creating high unemployment rates among women. In terms of research and development, women are underrepresented in Artificial Intelligence and account for only 26% of data and AI positions in the workforce (Heise et al., 2019). Therefore, a robust programme of inclusion and support in AI development and deployment is a moral responsibility for all stakeholders. Increasing representation and diversity in AI development is crucial to developing and deploying responsible AI products of value to all.

4.1.2. Designing safer and acceptable products

When products are designed based on the male norm, there is a risk that women and people of smaller stature will be harmed. Motor vehicle safety systems provide one such example. Because male drivers have historically been overrepresented in traffic data, seatbelts and airbags have been designed and evaluated focusing on the typical male occupant with respect to anthropometric size, injury tolerance, and mechanical response of the affected body region (Sugimoto et al., 2019).

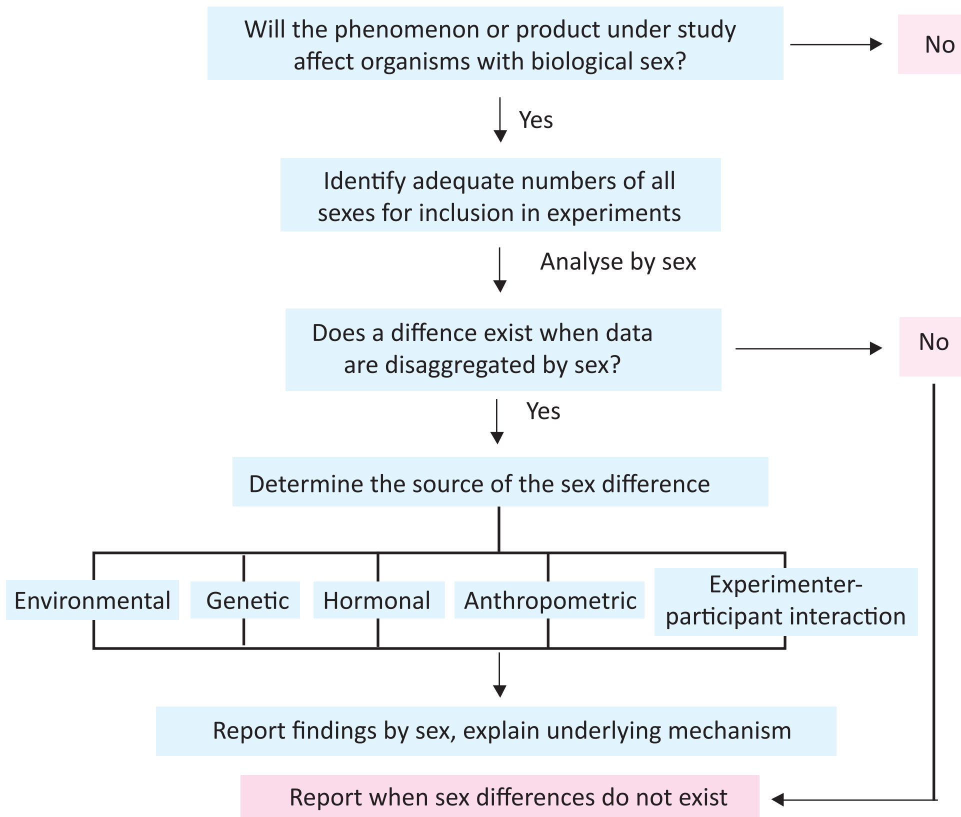
When national automotive crash data from the United States were analysed by sex between 1998 and 2008, data revealed that the odds for a belt-restrained female driver to sustain severe injuries were 47% higher than those for a belt-restrained male driver involved in a comparable crash, after controlling for weight and body mass (Sugimoto et al., 2019).

The subsequent introduction of a virtual female car crash dummy allowed mathematical simulations to account for the effect of acceleration on sex-specific biomechanics, highlighting the need to add a medium-sized female dummy model to regulatory safety testing (Shah et al., 2014). Beyond automotive safety systems, the importance of anthropometric characteristics, such as the carrying angle of the elbow or the shape and size of the human knee, can be used to guide sex-specific design for artificial joints, limb prostheses, and occupational protective gear (Prates et al., 2019).

4.1.3 Reducing Gender Bias in AI

Alarming examples of algorithmic bias are well documented. For example, Google Translate defaults to male pronouns when translating gender-neutral language related to science, technology, engineering, and mathematics (STEM) fields. When photographs depict a man in the kitchen, automated image captioning algorithms systematically misidentify the individual as a woman (Parker et al., 2021). As AI becomes increasingly ubiquitous in everyday lives, such bias, if uncorrected, can amplify social inequities. Understanding how gender operates within the algorithm context helps researchers make conscious decisions about how their work functions in society.

Figure 2 is the draft pathway to gender inclusion and science and engineering research support.

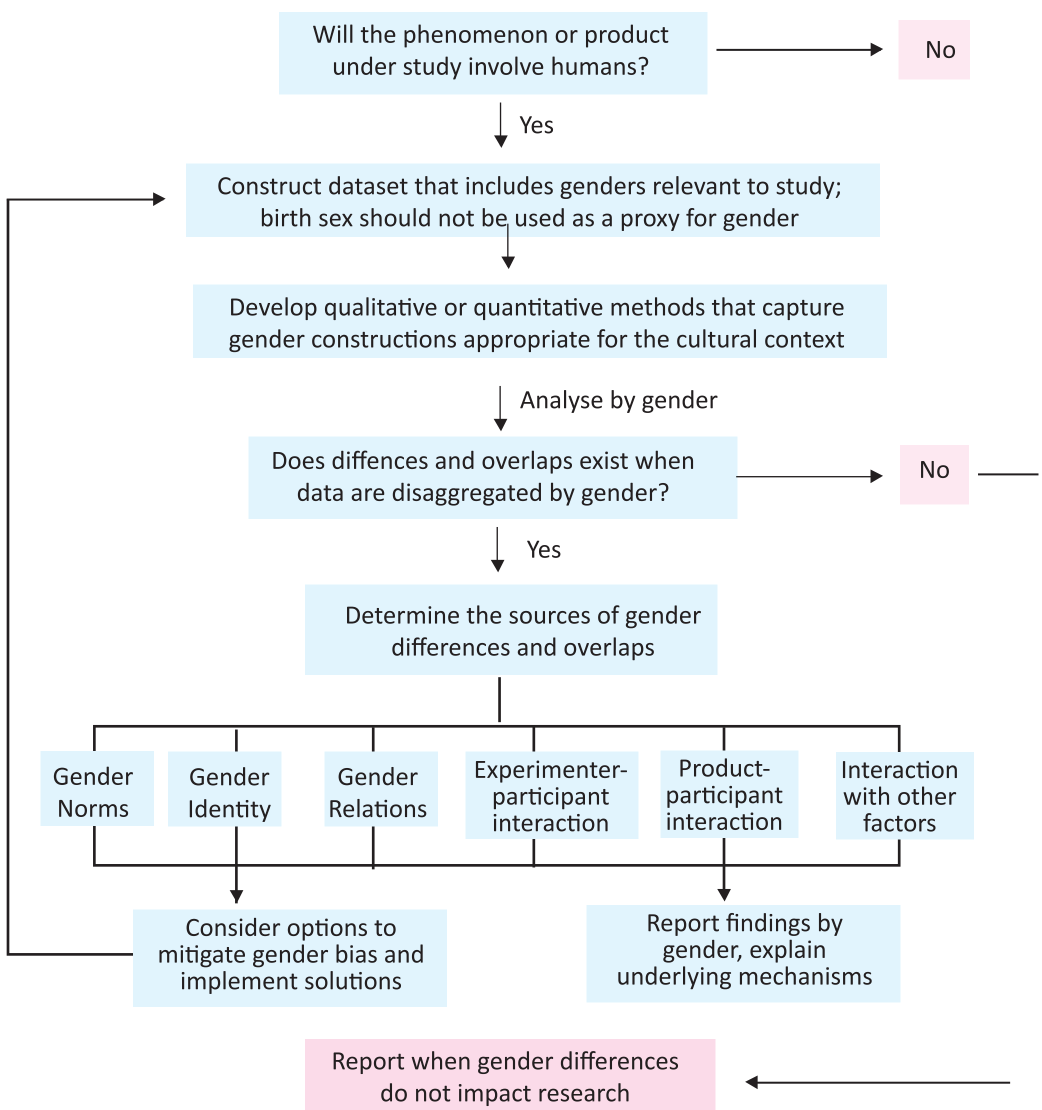


Source: Tannenbaum et al., (2019)

Fig. 2: Sex analysis and reporting in science and engineering.

4.1.4 Combating Stereotypes

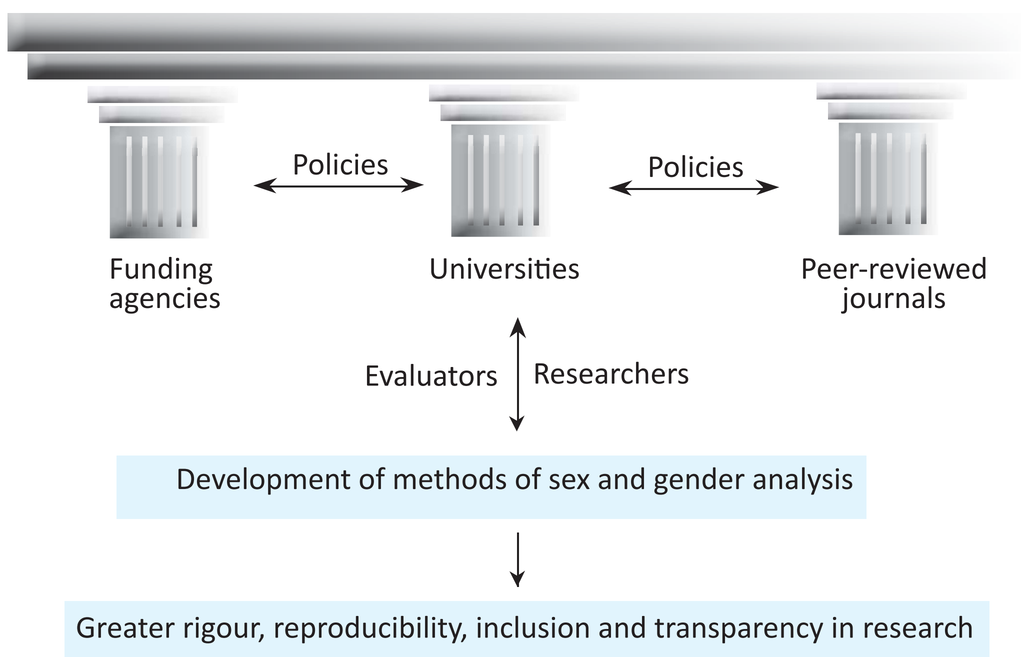
Analysing gender in software systems is one issue; configuring gender in hardware, such as social robots, is the focus of this section. Until recently, robots were largely confined to factories. Most people never see or interact with these robots; they do not look, sound or behave like humans. But engineers are increasingly designing robots to assist humans as service robots in hospitals, elder care facilities, classrooms, homes, airports, and hotels. The field of social human–robot interaction examines, among other things, when and how 'gendering' robots, virtual agents, or chatbots might enhance usability while, at the same time, considering when and how to avoid oversimplifications that may reinforce potentially harmful gender stereotypes (Buch et al., 2019). Machines are, in principle, genderless. Gender, however, is a core social category in human impression formation that is readily applied to nonhuman entities. Thus, users may consciously or unconsciously regard gender machines as a function of anthropomorphizing them, even when designers intend to create gender-neutral devices. Gender reporting in science and engineering should follow the pathway shown in Figure 3 (Tannenbaum et al., 2019).



The two figures (Fig 2 and 3) show the decision tree representing a cognitive process for analysing sex. A 'no' indicates no further analysis is necessary. A 'yes' suggests the next step that should be considered (Tannenbaum et al., 2019).

4.1.5 Gender and Science Policy

Policies are drivers of discovery and innovation that can enable sex and gender analysis in science and technology. To push forward rigorous gender analysis, interlocking policies need to be implemented by three pillars of academic research: funding agencies, peer-reviewed journals, and universities. The key decision tree for gender science policy is shown in Figure 3 (Bahamonde et al., 2016). Government-led funding agencies have taken the lead by asking applicants to explain how sex and gender analysis is relevant to their proposed research, or to explain that it is not.



Source: Bahamonde et al., (2016).
Fig. 4: Three pillars of science and engineering infrastructure.

In summary, the following gender gaps are found in AI systems;

- Use of logos or symbols
- Lack of gender analysis and reporting (gender inclusion statistics)
- Lack of Gender inclusion plan (experts, recipients, and composition), and
- Lack of Capacity building inclusion plan.

4.2 The rationale for Carbon Footprint Reporting

Climate change has been occurring since the Industrial Revolution in the 1820s (Fursin, 2020). Anthropogenic activities that solely rely on fossil fuels have exacerbated the rate of Greenhouse gases (GHGs) and the greenhouse effect on the earth in general. There is increasing evidence that early and rapid reductions in GHGs emissions are needed to avoid the significant impacts of climate change. Moreover, the Stern report on the Economics of Climate Change provided evidence that "the benefits of strong and early action far outweigh the economic costs of not acting" (Miao et al., 2019).

There is a need to reduce the overall carbon emission by tracking carbon footprints left for each activity, process, and way of life. There are several ways to reduce one's greenhouse gas footprint: choosing more energy-efficient eating habits, using more energy-efficient household appliances, increasing fuel-efficient cars, and saving electricity (Gahne et al., 2020). Although the presence of intangible assets complicates calculating carbon footprint, consistent data collection and existing methodologies can aid in getting the projected carbon footprints of both individuals and organizations (Loyarte-Lopez et al., 2020)

Responsible carbon footprint reporting will entail recording all activities during the project's entire life cycle to determine the equivalent CO_2 emission for all activities. The project life cycle includes activities in developing, deploying, and MEL process in using AI in AFS. After the advent of deep learning (DL), the use of computing power (now computers) has grown exponentially, doubling every 3.4 months (Amodei and Hernandez 2018), as specialized hardware for training large AI models has become the focus of the research field (Hooker 2020).

The increase in power consumption associated with training larger models and the widespread adoption of AI has been partially mitigated by improvements in hardware efficiency (Ahmed and Wahed 2020; Wheeldon et al., 2020). However, depending on where and how energy is extracted, stored, and distributed, the proliferation of computationally intensive AI research could significantly negatively impact the environment (Lacoste et al., 2019).

The carbon footprint represents the GHG emissions of a device or activity expressed in CO_2 equivalent (CO_2eq) (Crawford and Joler 2018; Malmodin and Lunden, 2018). The carbon footprint estimate includes information on the carbon emission intensity of electricity or energy consumption and the efforts to offset the carbon emissions of the various actors involved in the activities (Mattew et al., 2008). Data centers may not be a big deal when reporting carbon emissions due to the plethora of artefacts and actions embedded in some form of AI and its multi-layered manufacturing processes (Russel 2019).

Data collection and storage, material production and transportation, and AI (ML) model training and inference are critical elements of AI's carbon footprint reporting. Therefore, these factors, activities, and processes are all considered in responsible carbon emissions reporting. Masanet et al. (2020) argue that to assess AI activities' energy consumption and carbon footprint, it is essential to distinguish between the two main computational phases at the heart of the methods (AlJarrah et al., 2015).

Recently, several approaches to monitoring and estimating GHG emissions from AI research activities have been proposed. These include reporting floating point operations (Lacoste et al., 2019; Schwartz et al., 2019; Henderson et al., 2020), hardware type and hardware load, or "processor multiplied by speed" and computation time" (Thompson et al., 2020, 10), the data centre used when training the model, as well as the power sources that feed the electrical network (Schwartz et al., 2019; Anthony et al., 2020), number of experiments required when building a model (Schwartz et al., 2019; Strubell et al., 2019), and the length of time a model is trained, because of emission intensity carbon/carbon can change during the day (Anthony et al., 2020).

Of these approaches, two recent efforts stand out for their generalization and/or ease of use, namely Henderson et al., (2020) "Experiment-impact-tracker" and Lacoste et al., (2019) Machines calculate machine learning emissions.

The first approach rests on a comprehensive framework available on GitHub (Henderson et al. 2020), specifying the relevant data to collect during and after model training phases to assess the related GHG emissions as follows:

a) Central processing unit (CPU) and graphics processing unit (GPU) hardware information;
b) Experiment start and end times;
c) The energy grid region the experiment is being run in (based on IP address);
d) The average carbon/emission intensity in the energy grid region;
e) CPU- and GPU-package power draw;
f) Per-process utilization of CPUs and GPUs;
g) GPU performance states;
h) Memory usage;
i) The real-time CPU frequency (in Hz);
j) Real-time carbon intensity.
k) Disk write speed.

Responsible AI carbon footprint reporting will entail providing information on the items listed above, which many authors or researchers avoid or are not aware of. Using Lacoste et al.'s carbon impact calculator, there is a need to provide cloud provider information like Microsoft Azure and the base of the cloud provider - Microsoft Azure, US -West.

One available tool is the code carbon tool, a lightweight software package that integrates into the python codebase to estimate the CO_2 produced to execute the code, and how you can lessen your emissions. The selection of cloud providers is important in the model training and deployment. Some cloud providers are located in some regions of the world that is not eco-friendly with respect to the equivalent emission from such providers. The selection of cloud providers with low equivalent CO_2 emissions would be preferred to those with high equivalent CO_2 emissions.

4.3 Ethical consideration in non-model training-based activities

Other AI development and deployment activities require responsible behaviour in line with climate mitigation activities. Alternative use of non-high emitting CO_2 transportation pathways like walking, paperless information communication, virtual workshops and training, alternative power systems (Solar power systems), and building designs with high natural lightening should be considered in the selection of meeting places to avoid high power consumption.

5. Problem and Potential areas of Agriculture and food system for AI application.

Many problems are facing the AFS sector in Africa that require urgent interventions to meet SDG 2 by 2030. This section discusses the problem areas where AI innovations can be deployed to transform AFS in Africa. Ben-Ayed and Hanana (2021) identified four problem categories where AI can be applied in AFS to include: preproduction, production, processing, and distribution. In the same vein, the UNCTAD (2017) and FAO (2019) align with the four dimensions of food security: availability, access, use/utilization, and stability to identify the key problem areas where AI can be applied in AFS. For ease of administration and management, we adopt the UNCTAD and FAO classification to analyse these problem areas.

5.1 Availability

Availability addresses whether or not food is actually or potentially physically present, including aspects of production, food reserves, markets and transportation, and wild foods.

- ***Low agricultural production and productivity:*** Companies and people in African countries are still utilizing rudimentary and obsolete equipment, tools, and outdated technologies in their production systems thereby leading to low agricultural productivity, wastage of raw materials and resources, and generation of excessive wastes. Agricultural production and productivity in Africa remain lower than in the rest of the world (Bjornlund et al., 2020). This is attributed to factors inherent to Africa and its people, such as climate, soil quality, use of crude implements, low-value addition, and pests and diseases. Breeding activities by classical methods take years to establish new crop varieties. Farming practices and extension service delivery are still rudimentary.

Machine failure can lead to wastage of work-in-process inventory and loss of productivity. Productivity in AFS in much of Africa has long been a concern, both because of the low levels of land and labour productivity across much of the continent, and because productivity increases have been slow. This concern has grown with the resurgence of interest in agricultural growth in Africa seen since the 2003 Maputo Declaration (Wiggins, 2015).

Interest in agricultural productivity coincides with discussions about overall economic growth across many African countries, where the welcome news of renewed growth has often been tempered by observations that economies are growing, but not transforming. Growth has been largely in primary production with only small changes to the structure of economies and with correspondingly weak development of manufacturing and high-value services. The 2014 African Transformation Report (ACET, 2014) sees agriculture as an example of slow productivity growth, hence the need for an urgent intervention to turn the tide of decreasing productivity to increasing productivity.

- ***Soil degradation:*** Genetically improved crop varieties might not increase yields if constraints such as low soil fertility are not overcome. Fertile soils play a pivotal role in sustaining agricultural productivity and thus food security. The focus on innovations and technological developments is more on crops and fighting pests and diseases and less on sustainable soil management practices (UNCTAD, 2017). However, healthy plants grow on healthy soils that are less affected by pests and diseases. Soil degradation resulting from erosion and poor land-use lead to loss of soil fertility and low agriculture productivity. This complex phenomenon also has impacts on the ecosystem services such as pollination.

Climate change also impacts negatively on the soil properties causing rapid moisture and nutrient loss. In most SSA, soil degradation potentially undermines efforts towards sustainable agricultural production and so poses a major threat to the future of agriculture (Sullivan, 2004). Ever since mankind started agriculture, soil erosion has been the single largest threat to productivity (Sunday et. al., 2012).

Poor soil management and rudimentary farming methods have highly accelerated soil degradation hence affecting the health of crops and ultimately leading to low yields.

- ***Challenges in insect pest and diseases detection:*** Insect pest infestation and diseases are among the most alarming problems in the African agricultural system and have led to heavy economic losses (Ngumbi, 2017). There is increasing pressure from re-emerging and emergent pests and diseases in crop and livestock production across Africa. Such emerging pressures are likely to become more problematic with weather variability and climate change. Over decades, researchers have tried to mitigate these menaces by developing computerized systems that could identify active pests and diseases and thus suggest control measures on time.

The use of chemicals has also been prominent over the years although it has been blamed for the rising number of cancers (Rifai, 2017). According to Bannerjee et al., (2018), significant expertise and experience are required to detect an ailing plant and to take necessary steps for its recovery.

- ***Difficulties in livestock management:*** Feed shortage, limited knowledge by farmers in livestock production, poor genetic potential of indigenous livestock breeds, pests and diseases, vagaries of weather, and land shortage are the main constraints affecting livestock production in Africa. Despite the enormous potential that livestock production holds as a source of food, income, foreign exchange, hides and skin, manure, draught power, and risk reduction in times of crop failure.

  Many african farmers and their families still suffer from nutritional deficiencies that livestock can quickly provide despite having livestock. This is partly due to poor management practices that reduce availability, hence the need to adopt modern livestock management techniques to increase productivity. With the global population rising and fewer farmers available to care for livestock, each farm needs to increase productivity with limited resources.

5.2 Access

This area explores whether or not households have sufficient access to quality, quantity, and diversity of nutritious foods.

- Supply chain inefficiencies: Africa's food supply chains are vulnerable to many disturbances and disruptions. These include biotic, abiotic, and institutional risk factors. The emergence of the COVID-19 pandemic, which has not only interrupted but also tempered with food supply chains, has compounded these vulnerabilities. According to FAO (2020), there is not a shortage of agricultural commodities across the world but rather a bottleneck of access and logistics to reach consumers. With over 60% of the African continent's population in rural areas and dependent on smallholder farming, the risk to food supply chains, market access, and nutrition especially during the COVID-19 pandemic is high. There has been lockdowns and restriction of movements of persons and commodities within and among countries. Again, the non-tariff barriers restricting the movement of essential items within Africa demotivate the tenets of the African Continental Free Trade Area (AfCTA).

Africa's long supply chains create delays and produce often gets spoiled or loses its value. It is estimated that 30 to 50% of fresh produce is lost through poor handling and limited cold chain facilities (Nieuwoudt, 2019). This leads to increased prices, passed on to urban centres' consumers who consume 80% of the food produced. The many intermediaries and limited technology, create poor visibility in the supply chain, and farmers rarely know the price of their products before the sale.

5.3 Use/Utilization

It analyses whether or not households are maximizing the consumption of adequate nutrition and energy determined by knowledge and habits as well as the ability of the human body to take food and convert it.

- Inadequacies in food processing and safety: Food processing is a significant driver of local economies, creating supplier linkages for millions of small-scale farmers and helping elevate rural incomes. One of Africa's greatest challenges in AFS development is the inability to process their primary agricultural products to get the full premiums in price, create jobs and sustain their economies. Yet, the few and growing local processors often have difficulties producing high-quality, affordable, and nutritious products that meet food safety standards and regulatory requirements due to a lack of technical and business knowledge, investment, and technology. Intra-African food demand is projected to increase by 178% by 2050 and African diets are changing with more demand for processed products and meats as a complement to traditional staple crops such as maize, sorghum, cassava and pulses (Gross, 2020).

- ***Poor nutrition and increased incidences of malnutrition:*** According to the State of food security and nutrition report, 2020, beyond hunger, a growing number of people have had to reduce the quantity and quality of the food they consume (FAO et al., 2020). Two billion people, or 25.9% of the global population, experienced hunger or did not have regular access to nutritious and sufficient food in 2019. This situation could deteriorate further especially with the menacing COVID-19 situation if immediate actions are not taken.

  The alarming trends in food and nutrition insecurity contribute to increasing the risk of child malnutrition, as food insecurity affects diet quality, including the quality of children's and women's diets, and people's health in different ways. It is not surprising that the burden of child malnutrition remains a threat around the world. In 2019, 21.3% (144 million) of children under 5 years of age were estimated to be stunted, 6.9% (47 million) were wasted and 5.6% (38.3 million) were overweight, while at least 340 million children suffered from micronutrient deficiencies.

  Projections for 2030, even without considering a potential global recession, serve as an added warning that the current level of effort is not anywhere near enough to end malnutrition in the next decade unless there is significant transformative change in the AFS.

5.4 Stability

Food stability covers household's food security at all times. Stability issues refer to short-term, medium to long-term instabilities that can be caused by climatic, economic, social, and political factors.

- ***Poor weather monitoring, forecasting and disaster prediction preparedness:*** Africa is among the most impacted by erratic weather and climate change disasters. The capacity to collect, analyse and use climate data has been a major challenge over the years as governments use obsolete equipment and have low technical capacity for this purpose.
  The challenge of weather forecasting at the temporal and spatial levels in most African countries is severely affecting the predictive capacity of countries leading to their inability to adequately prepare for extreme weather events. There are several critical gaps in the process of climate information generation, processing, and dissemination (World Meteorological Organization, 2014).

  The precise impacts of climate change on AFS vary spatially, but two general predictions are greater variability in agricultural production and possibly a decline in crop productivity (Schlenker and Lobell, 2010).

- ***The unpredictability of crop and livestock yields:*** Many African farmers are unable to accurately predict yields of their crops and livestock and are therefore not in a position to know how produce will be apportioned for processing, sale, or storage. Yield variations from season to season have led to various associated problems such as price fluctuations, post-harvest losses, gluts, and panic sales. The amount of food lost each year due to postharvest losses and wastage is enough to feed the total number of undernourished people globally. In SSA alone, which unfortunately is home to over 230 million people suffering from chronic undernourishment, 30-50% of production is lost at various points in the value chain (Deloitte and Touche, 2015).

- Poor use of evidence and data for policy decision-making: African governments have rarely used robust data and research evidence in policy decision-making due to inadequate capacity at individual, institutional and systemic levels; poor research infrastructure; lack of political goodwill, and ineffective linkages among research, industry, and government among others.

  African countries have been very proactive in developing policies based on societal needs but the greatest challenge is that most of these policies are not based on robust research evidence and data hence implementation usually becomes difficult (Ozor et al., 2014).

5.5 Potential Areas of Artificial Intelligence Application in Agriculture and Food System in Africa

The potential areas of artificial intelligence application are discussed in this section according to the problem areas identified under the four dimensions of AFS already described in sections 5.1 to section 5.4 namely; availability, access, utilization, and stability.

5.5.1 Potentials of AI in food availability

AI can provide innovative solutions to improve production systems and hence productivity. AI can be applied in precision farming and predictive analytics to increase production and productivity. AI applications and tools have been developed to help farmers reduce inaccuracies and control farm practices by guiding water management, type of crop to be grown, optimum planting, crop monitoring, weeding, pest and disease resistance and control, timely harvesting, nutrition management, and extension service delivery among others (Talaviya et. al., 2020).

AI has been used in plant breeding for optimal production and forecasting of crop yields under variable and changing climates. AI can help analyze historical reasons for failures and combine them with real-time data such as images from the production line to predict upcoming failures of machines. This increases productivity and more efficient utilization of power and reduces wastage in production systems.

AI algorithms using satellite images can determine the quality of soils in a particular area and the type of crops that can do well in such areas hence leading to optimal productivity. AI can support soil fertility nutrients mapping, and restoration, monitoring using imaging through drones, and generate information to guide food waste management such as recycling. The data captured through imaging by AI-powered devices can support high throughput phenotyping in research.

AI-based tools are used for pests and diseases detection, monitoring, and management through image processing which at the same time provide big data on pest distribution and incidence at the landscape, country, and regional levels. AI algorithms can detect the presence of pests and diseases using satellite images and send alerts to farmers for the timely implementation of mitigation measures. It will be possible to develop a Low Altitude Remote Sensing (LARS) for the recognition of early pest infestation.

AI and computer vision allow farmers to achieve this. They enable farmers to monitor their animals in real-time and results are forwarded to farmers' mobile phones. They also assume remote control of the farm's feeding, milking, and cleaning systems. They alert farmers on abnormal behaviour spotted within their livestock and their herd's overall well-being including sanitizing the herd's pens whenever necessary to minimize the risk of infections. Uganda for instance has embraced AI and ML to detect livestock diseases two days before they manifest, connect farmers to veterinary officers remotely and monitor animal movement to avert theft. The innovation, dubbed Jaguza Luganda, constitutes a chip with a sensor that is connected to a radio-frequency identification (RFID) reader, and users' mobile phones or computers (Koigi, 2019).

5.5.2 Potentials of AI in Food Access

Nonetheless, AI systems have the potential to mitigate some of these vulnerabilities across supply chains, and thereby improve the state of food security in Africa. The COVID-19 pandemic for example accelerated the application of technologies such as Food apps, drone and robot delivery technologies as new ways to get information and food to the consumer through AI technologies. UberEATS is now incorporating AI to make recommendations for restaurants and menu items and looking into the use of drones for their deliveries.

AI allows companies to predict consumer trends and patterns thereby helping them stay competitive within the market by adapting to different popular waves of various trends and making predictions about the market.

E-commerce platforms such as Twiga Foods have also been developed and used to market goods and services. They make use of disruptive technologies such as AI, IoT, and Blockchain to automate their distribution and market processes.

5.5.3 Potentials of AI in food Use/Utilization

AI directly impacts food processing and safety in five different ways namely: sorting packages and products, food safety compliance, maintaining cleanliness, developing products, and helping customers with decision making (Sharma, 2019). AI can maximize output and reduce waste through innovative sensor-based sorting machines, detecting and removing any types of foreign materials, reacting to changes in moisture levels, colours, smells, and tastes of foods, etc. AI will help inform decisions about 'cleaning' to improve sanitation and reduce the spread of pathogens and toxins in foods. It helps to reduce energy use and waste by advising against transporting food that may not be used at its destination.

AI can predict the ingredients from photos in a consumer's food journal. It will help to better capture food consumption, determine the nutrients and molecular structure of that food, and predict health outcomes of those dietary choices. Changes in consumer preferences are creating opportunities for AI in foods. An example is a growing demand for plant-based alternatives to meat protein as the world moves towards precision nutrition. Consumer acceptable taste and texture qualities have been achieved through AI.

5.5.4 Potentials of AI in food Stability

AI technologies could play a major role in fixing this problem. AI can enhance weather data collection and prediction and hence provide ample time for response. AI can enable farmers to understand the ever-changing weather conditions and be able to precisely plan for farm enterprises along the value chains thereby reducing losses from the vagaries of weather.

Forest officials can use ML to identify which crop species are most resistant to natural disasters such as droughts, hurricanes, floods, forest fires, etc. and make recommendations for breeding programmes. IoT sensors can be attached to various trees and be used to alert authorities in case of a wildfire. This ensures stability in the AFS. Yield prediction in crops and livestock is very beneficial for marketing strategies and cost estimation. ML is an important decision support tool for crop yield prediction, including supporting decisions on what crops to grow and what to do during the growing season of the crops to ensure maximum yields (van Klompenburg et al., 2020). Farmers use drones for livestock surveillance for monitoring pregnancies (Ben-Ayed, 2021).

Besides aiding in the collection of data, analyses, and use in decision-making, AI can also be used for regulatory purposes. Under the theory of the limited rationality model, public policymakers have different limitations for the construction of public policies, especially those that require a high level of complexity due to the large number of variables that they present (Shaffer, 2017).
For this reason, some research has been carried out using AI tools such as expert systems, case-based reasoning, artificial neural networks, agent-based models, cellular automata, evolutionary algorithms, and agrarian public policy variables to improve the decision-making process to help public policymakers (Sanchez, 2020).

AI can also be used in understanding the impact of previous policies and predict the performance of new ones. ML can help analyze previous policy actions automatically and at scale by improving computational text analysis. Such applications will enable governments to effectively leverage AI for the development and stability of the AFS.

6. Challenges to AI application in Africa's Agriculture and Food System

There are many challenges affecting the use of AI in agriculture and food systems; these are discussed in this section.

6.1 Lack of diverse datasets specific to localized issues

The lack of publicly available datasets contextualized in Africa and Africa's agriculture to train algorithms has hampered the use of precision agriculture tools on the continent. The dataset contains images used to train the algorithm. When the algorithm is exposed to image processing, it can recognize patterns in the image.

The ability of algorithms to recognize patterns enables the detection of plant diseases. However, image processing requires high-resolution images for algorithms to manipulate and store information. High-quality images and no-cost factors limit access to datasets and limit algorithm training. In addition, published datasets do not meet the demand for specialized datasets that are specific to local issues. Therefore, the lack of contextualization makes it more difficult for the algorithm to detect, limiting the usefulness of datasets in precision agriculture.

6.2 Privacy concerns

There are privacy concerns arising from the data and images captured by satellites and drones to train the algorithm. In most countries, privacy breaches from existing data protection legislation are barriers to the use of drones and satellites in smart agriculture. These laws make it difficult to violate the right to privacy and consent without legal justification.

Approval for the use of drones and satellites is subject to the farmers' ability to prove that their right to privacy has not been violated. Satellite-based data helps track large farm problems, and drones support operational monitoring. These drones also rely heavily on training datasets that require copyright-free images.

Copyright laws limit data access for AI, unless content owners assign a creative commons license to use the images, access is restricted without consent.

6.3 Low digital literacy

Farmers may not know how to access or use the available AI applications or how to use these technologies to support precision agriculture. Technology uptake is usually limited by the level of education and knowledge of the farmer, which affects the ability to apply the technology at the farmer level. This limitation leads to the failure of sustainable agriculture. Sustainable agriculture means meeting existing food needs without compromising environmental health and economic equity.

By integrating AI-enabled technology into agriculture, farmers can assess crop sustainability (Walker, 2019). Therefore, if farmers do not know how to use these technologies, they miss the benefits of forecasting and evaluation that help promote agricultural sustainability. In addition, the lack of digital literacy leads to the adoption of wrong technology and hence failure of results (UNEP, 2021).

6.4 Gender gaps in AI in Africa

With the advent of technology, the gap between men and women is widening, if not worsening. With new tools, for example, a biased algorithmic identification method for mislabelling, that leads to the algorithm misclassification of women in a particular profession, flawed keyword searches in information and communication technology (ICT), and sexist terms.

The persistence of inherent stereotypes in Artificial Intelligence (AI) including AI assistants with female voices and representation of AI in media on a sexist scale has called into question the assumption of neutrality of algorithms and the potential for harm in the future. While much has been said about the global AI gender gap, the African AI landscape lies largely unexamined in its contribution to the gender gap in AI.

In a report of an experimental study of female representatives in African AI, based on data collected on the workforce composition of African-based AI companies and projects; the gap between men and women in AI in Africa stands at 71-29% compared to the global gender gap of women in AI which stands at 78-22% as of 2018 (Heise et al., 2019).

The proportion of female participation per industry differs from corporate services, healthcare, and agriculture having the smallest gender gaps and entertainment and environmental conservation having the widest.

6.5 Environmental concerns

Greenhouse gases absorb radiant energy in the infrared range to raise the earth’s temperature and enable the greenhouse effect (Pham et al., 2018). Although some emissions are natural, the rate of production has increased because of anthropogenic activities. The primary emitters of GHGs are fossil fuel use in electricity, heat, transportation, and using chlorofluorocarbon (CFC) products. The most common GHGs are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and many fluorinated gases (Radford et al., 2018). Carbon footprint is the numerical quantity of GHGs gases that a single entity emits.

The calculations can be computed ranging from a single person to the entire world (Rangan et al., 2020). The sixth annual assessment report by Intergovernmental Panel on Climate Change (IPCC) presents key scientific findings linking the increase in anthropogenic GHGs emissions to current climate change (IPCC, 2021). Achieving the 1.5 °C global temperatures relative to pre-industrial levels would require an immediate reduction in the emissions of GHGs (Rangan et al., 2020; IPCC, 2021).

Artificial intelligence training is an energy-intensive process. New estimates indicate that training a single AI will produce 284 tonnes of CO_2 emissions. This is five times the lifetime emissions of an average car (Coleman et al., 2020).

AI can also streamline logistics, reduce the materials needed to make things, and otherwise reduce carbon emissions. For example, according to a BCG study, AI could reduce global greenhouse gas emissions by 5% to 10% by 2030, equivalent to a 2.6 to 5.3 gigaton reduction (Cook, 2019). AI (in the sense of both training models and applications) can consume enormous amounts of energy and generate GHGs emissions (García Martín et al., 2019; Cai et al., 2020). Therefore, systematically and accurately measuring the carbon footprint of AI is key to responsible AI implementation.

7. Opportunities in Artificial Intelligence for Africa's Agriculture and Food Systems

Several opportunities exist in developing, deploying, and using AI in Africa's agricultural and food systems. Some of the challenges identified are the lack of capacity, data, right regulatory policies, gender gaps, environmental concerns, and the overall enabling environment, which affects the successful implementation of AI in AFS. These challenges provide an opportunity to develop and deploy homegrown artificial intelligence for Africa's agriculture and food systems.

The following sections will now focus on the opportunity areas for leapfrogging agriculture and food production in Africa using AI. The capacity to develop, deploy, and scale-up AI involves various areas; these areas are grouped as tangible resources (data, technology, basic resources), human capacity (technical skills, business skills), and intangible resources (inter-departmental synergy, organizational change).

7.1 Availability of data

Based on a recently published study by the MIT Sloan Management Review, data are considered by managers as one of the key enablers in leveraging the potential of AI (Ransbotham et al., 2018). While organizations have traditionally focused on structured data in order to guide business decisions, today's organizations capture a large diversity of data stemming from multiple sources and in different formats (Kersting and Meyer, 2018). In fact, the availability of high-quality data is considered critical, as it is used to train AI algorithms. A recent study by Ransbotham et al. (2018), found that pioneering organizations in AI follow a common understanding within their management teams which regards data as a corporate asset. The convergence of big data with AI has emerged as one of the most important developments and is shaping how firms drive business value from their data resources (Bean, 2017).

When it comes to developing AI applications that can deliver value, the quality of the data that are fed into such algorithms is of great importance. Since AI systems require massive training data sets, and applications effectively "learn" from available information in a manner similar to the way humans do, there is a high requirement for large amounts of high-quality data. Hence the opportunity for data scientists to be trained to acquire relevant skills in building data banks for Africa's AI development and deployment.

Universities and various institutions can reframe their curriculum to incorporate the teaching and storage of big data unique to Africa for the deployment of AI. Providing such a data bank will ensure that AI in Agriculture and food systems are responsible.

7.2 Availability of technology

AI technologies also put pressure on organizations to invest in technologies that can quickly process data and run complex algorithms. Common approaches include the use of GPU-intensive clusters and using parallel computing techniques to deal with the processing power required (Nurvitadhi et al., 2017). Many organizations are also adopting cloud-based solutions to deal with the large cost associated with AI infrastructure, while a new market for integrated cloud services that allow complex AI methods to be applied through simple API calls has gained prevalence over the last years (Del Sole, 2018). There are a lot of tech-investment opportunities for Africa to develop homegrown technologies that support the use of AI in agriculture. This essentially translates to infrastructure investments being made through the whole pipeline from ingest to inference, from storage, transfer through high bandwidth networks, to processing power. The technological infrastructure is also highly dependent on the type of techniques that are used, which means that organizations can end up having to invest in several different supporting technologies.

7.3 Improved infrastructure

Apart from the opportunity in data and the technological infrastructure to support AI, organizations and governments need to be able to provide time and financial resources to allow such initiatives to deliver expected outcomes. As most organizations are just now experimenting with AI, the vast majority of initiatives will need some time to mature before being released and yielding value (Ransbotham et al., 2018). Adding to time requirements, another important aspect that organizations must invest in is providing adequate financial resources to allow AI applications to develop.

In a 2017 study by McKinsey, the majority of respondents reported that less than one-tenth of their digital technology spending was on AI initiatives (Chui and Malhorta, 2018). Hence there are opportunities to leverage external donors to fund research in AI for Agriculture and food systems.

7.4 Increase in technical skills

When referring to technical AI skills, we mean those necessary to deal with the implementation and realization of AI algorithms, manage the infrastructure to support such initiatives and introduce and ensure AI applications adhere to goals. More specifically, algorithm developers are necessary in order to utilize the latest AI research and transform it into repeatable processes through mathematical formulas that can be implemented through hardware and software (Specor and Ma, 2019). It has been suggested that most careers in technical aspects of AI will require individuals with a strong background in statistics, probability, predictions, calculus, algebra, Bayesian algorithms, and logic. In addition, a good background in programming, logic, data structures, language processing, and cognitive learning theory has been highlighted as an essential technical AI skill (Lesgold, 2019).

A recent article in the MIT Sloan Management Review presents three key roles that will emerge as technical profiles in the age of AI: trainers, explainers, and sustainers (Wison et al., 2017). Trainers are concerned with teaching AI systems how they should perform, and include tasks of helping service chatbots, for instance, identify the complexities and subtleties of human communication. Explainers bridge the gap between technologists and business managers by providing clarity regarding the inner workings of AI systems to non-technical audiences.

Finally, sustainers ensure that AI systems are operating as expected and that any unanticipated consequences are addressed appropriately. Each of these three roles includes a list of more detailed job functions that are already becoming critical for contemporary organizations.
While these skills are currently scarce in the market, it is argued that they will gradually become more common, as higher education and online training courses are emerging, making this resource a commodity across firms over time (Danyluk and Buck, 2019).
Therefore, there is a big opportunity for the private sector, academia, and government to invest in training trainers. The job opportunities created are a source of joy for those trained, especially for the growing youth population.

Incorporating powerful AI tools into the day-to-day work of companies will require individuals who have a thorough understanding of technology and business strategy. Continued progress in AI will build on predictive analytics and machine learning capabilities, and professionals who know methods for gathering extensive data and using it to plan will have a leg up. These analytics-savvy individuals are only becoming more crucial to organizations as they use quantitative information to find business intelligence and function with greater agility.

Data-driven skills are vital for management analyst, logistician, or computer and information systems manager roles. All these positions and more will have an important part to play in the increasing reliance on the speed and efficiency of AI-assisted decision-making and implementation (Zhuang et al., 2017).
Professionals interested in seizing AI-driven business opportunities should develop a solid grounding in big-data tools and strategies. Working toward a business analytics master's degree could prepare them to lead the way in implementing new technology to meet an organizational need.

Online courses at Villanova University provide an education that emphasizes both the latest in technology and best practices for business success. This will assist students to discover how to build data models, perform structured analysis, and use analytical data mining and optimization methods. With knowledge of how analytics empower more innovative business strategies, graduates are well-positioned to push forward the next steps of AI applications within their organizations (Zhuang et al., 2017).

7.5 Remote agricultural operations

AI can help farmers reduce the cost of carrying out and monitoring farm work for large-scale farming. AI-supported smart tractors and robotics(“agribots”) can be deployed to perform certain functions, e.g., harvesting large volumes of crops, possibly at a higher speed and volume than human labour would (Suiz-Rubio and Rovira-Mas, 2020). In livestock farming, drones mounted with cameras or sensors can gather information on the number of animals, unusual livestock movements, and animal health.

7.6 Weather forecasting

AI may use the data from past weather events to predict future weather (Dewitte et al., 2021). Weather determines the best time for planting, fertilizing, spraying, irrigating, and harvesting crops (Walker 2019).

Hence, forecasting weather can allow farmers to decide when to carry out agricultural processes to maximize their crop yields. Predicting rainfall, for example, can inform farmers’ decisions regarding irrigation which can prevent them from wasting limited water resources.

7.7 Enabling policies and institutions

All stakeholders in AI implementation value chain have an excellent opportunity to develop and deploy policies and the right institutions for responsible artificial intelligence in agriculture and food systems. These policies will enable proper gender inclusion and support, environmental protection, privacy, and intellectual property protection, and improved STEM uptake.

STI policies should be modified to provide the needed tracked training in AI. Policymakers have an opportunity to push legislation on data justice and sector-focused policies.

7.8 Increased youth and gender support

Responsible AI will assist in promoting youth and gender diversity and inclusion. Responsible AI in agriculture and food systems will mean increased support for women's participation in STEM as it is the driver of AI growth. It will give female scientists and AI leaders in business and society more chances, thus highlighting opportunities for women in AI and removing the negative stereotypes about females not belonging to STEM.

The new generation of female scientists is inspired, and talented women who are attracted to a workforce that exhibits gender inclusivity. It will create mentorship opportunities with training programmes, thus building the needed capacity and capability.

Young people are often more ready and eager to master these new technologies and apply them to agriculture to increase productivity and solve challenges (FAO, 2020). At the same time, these technologies can help demonstrate to youth how agriculture can be a viable and profitable business opportunity, increasing the desire to choose agriculture-related career paths, in lieu of alternatives youth might otherwise be seeking.

Motivated by the promises of digital tools for the modernisation of the agro-food sector despite their limitations and by the business opportunities that their use could generate, many young African software developers and entrepreneurs have joined the digital agricultural space. However, most of them face serious challenges to grow their businesses and offering sustainable value to the agricultural sector.

The responsible deployment of AI in Agriculture will solve and empower these youths.

8. Conclusion

The ability to enhance the performance and sustainability of agricultural food production systems globally depends on developing a deeper understanding of the linkages between innovation inputs and outputs and diffusion pathways in the sector.

AI can play a key role in helping us understand these diffusion pathways in the agricultural sector and the crucial process of connecting African farmers to new markets and new sources of knowledge from other sectors. It is only then will it be possible to fully leverage the potential of agricultural innovation, reverse persistently low levels of agricultural productivity, and ensure a sustainable global food supply.

In this regard, AI is an invention in the methods of invention that can fundamentally increase the productivity of scientific R&D and generate important spill-overs for the sectors using that knowledge Artificial Intelligence is a viable tool to leapfrog Africa's Agriculture and food production to feed millions, improve Africa's economy, and overcome the effects of climate change if applied responsibly.

Responsible AI use in Africa's agriculture requires critical legislation, capacity building, removal of gender bias, ethical standards for practice, environmentally friendly implementation, and AI-friendly policies. Indeed, artificial intelligence is vital as farmers battle the effects of climate change with improved crop yield and weather forecasting.

All stakeholders, the academia, government, private sectors, and non-governmental agencies, must synergise and put up a clear responsible AI policy and plans. The universities should develop innovative curricula focused on AI development and deployment. Donor funds meant for sustainable development and deployment of responsible AI should be used judiciously in achieving the goals and objectives of such funding; this will assist in attracting more funding for AI innovations.

The success of responsible artificial intelligence in agriculture and food systems depends on building the required capacity and capability. Training of more youths in STEM programs, including women, will assist in developing the needed skills that are currently unavailable. A data bank of all AI experts and an integration of experts from social science, agriculture, and engineering will positively affect the application of responsible AI in agriculture and food systems.

Finally, the responsible development and deployment of artificial intelligence in agriculture and food systems in Africa is the right and viable option to leapfrog agricultural and food production in Africa.

9. Recommendations for effective development, deployment, and scaling of responsible AI in AFS

The review informs the following recommendations of responsible artificial for Africa's agriculture and food systems. The recommendations are classified into four (4) areas, namely: financial support, capacity to develop and deploy AI in agriculture and food systems, infrastructure, institutional synergy, and strengthening STI policy

Recommendation 1: Strengthening the capacity to develop, deploy, and upscale AI in agriculture and food systems

There should be urgent investment in developing the requisite skills for developing and deploying artificial intelligence for Africa's agriculture and food systems among all stakeholders in the agricultural sector. This involves building capacity in the educational sector through skill-based curriculum change to adapt to the immediate need in partnership with relevant private and public sector actors. Training and capacity building for AI developers are important in successful AI implementation in Africa.

Currently, Africa lacks the requisite capacity to develop homegrown AI for Africa's Agriculture. This is why the current program by IDRC and Sida is a step in the right direction in developing the capacity to create and deploy AI in Africa's agriculture and food systems through the AI4D Africa. The formation of AI labs and sponsorship of PhDs in AI are capacity-building actions that will ensure the deployment of responsible AI in Africa's agriculture and food systems. There should be an active drive in data acquisition relevant to Africa's environment to ensure just application of data in line with the six core pillars of data justice to increase the capacity to deploy AI in agriculture and food systems. African governments should establish an inclusive and protected data bank with crop, animal, soil, weather, and market information.

Efficient energy supply systems are important in developing a robust AI system. Member countries in Africa should support the establishment of efficient and sustainable energy supply to enhance technological development. Hence, it is recommended that there is a need to build the capacity of AI designers and developers to acquire the technical skills required for AI deployment.

Additionally, capacity in the area of information on Africa's agricultural landscape to inform responsible AI development should be built as a repository data bank accessible but not abused.

Recommendation 2: Strengthening Institutional synergy and collaboration

Responsible AI deployment needs the collaboration of relevant institutions; academia, private AI firms, farmers, government, and primarily private and public organizations. Such synergy will help in developing functional teams with a mix of skills and perspectives in Africa. These functional teams with strong analytical and technical experts will ensure that all initiatives on responsible development, deployment, and scale-up of AI in AFS are successfully implemented. Interdisciplinary teams are the backbone for introducing and developing robust algorithms responsibly. Such teams can develop and deploy standardized AI designs, enhancing the deployment of user-friendly designs with a high adoption rate.

There should be an active drive in data acquisition relevant to Africa's environment to ensure the just application of data in line with the six core pillars of data justice.

Recommendation 3: Increased funding of science, technology and innovation

Increased investments in agricultural R&D at the continent and national level will support STI. The constantly changing ecological, environmental, and biodiversity contexts require continuous research and development to produce inputs and disseminate knowledge that maximizes agricultural yields while safeguarding the environment.

China's government-sponsored R&D, which increased by 5.5 per cent annually between 1995 and 2000 and 15 per cent after 2000, was considered key to adopting advanced technologies by poor farmers (UNCTAD, 2015).

Globally, it has been estimated by FAO, IFAD and WFP that eradicating hunger by 2030 will require an additional $267 billion annually (FAO et al., 2015). Based on estimates of the United Nations Environment Programme green economy models, 0.16 per cent of global GDP devoted to sustainable agriculture per year ($198 billion between 2011 and 2050) could provide significant returns (UNCTAD, 2015).

Hence, member nations should increase funding or financial support for STI R&D, which will directly affect AI development in the agricultural sector to enable an increase in food production.

Recommendation 4: Strengthening the STI pro-AI policies in Africa

Policies can be powerful tools for African governments to promote technological development by encouraging innovation and investment. At the same time, as leading countries have shown, government engagement and experimentation with nascent technology can also be a powerful signal of trust and support for local companies.

According to African stakeholders, low government engagement, particularly at the policy level, has been a hindrance, and a stronger focus will encourage early adoption of AI. African governments should take a proactive approach and implement AI-friendly regulations, policies, and initiatives.

There are several areas relevant to the development of AI and robust digital economies where policy-makers should focus, according to Pillay (2020):

- **Data privacy and security** — A data privacy and security framework that individuals can trust encourages and empowers them to use AI-based solutions that require their data to work. Data privacy and security laws should aim to protect users' data without restricting moving data across borders.
  In drafting these laws, African regulators should learn from international best practices, which includes avoiding burdensome requirements that would foreclose the benefits of AI and put African companies at a disadvantage.

- **Cybersecurity** — African governments should adopt cybersecurity laws that provide for meaningful deterrence, incentivise investment, clarify legal responsibilities, and create effective and reasonable enforcement mechanisms. Additionally, authorities should help users understand and properly manage the risks inherent in using AI technology.

- **Digital strategies and cloud adoption initiatives** — Governments should develop national digital strategies and policies that foster widespread cloud adoption to democratise the use of advanced technologies.

- **Intellectual property** — Intellectual property laws that provide for clear protection and enforcement against misappropriation and infringement of technological developments, including proprietary algorithms, are indispensable to promote continued innovation and advancement in AI.

- **Procurement policies** — Public procurement regulations should enable the use of AI solutions to provide public services. By investing in public sector innovation, African governments will demonstrate their trust in AI and support the growth of local developers.

- **Industry-led standards and international harmonisation of rules** — IT organisations worldwide are developing international standards to ensure data portability, interoperability, and a smooth data flow. African governments should remain abreast of developments in this area and seek to adopt international standards and harmonisation rules as they become applicable.

Hence, Africa must develop the right policy and institutional landscape to create the enabling environment for the development, deployment, and use of responsible AI in Africa's Agriculture and food. Pro-AI policies drive robust digital infrastructure in higher education institutions, e-learning platforms, hardware, and broadband.

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