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LEVERAGING ARTIFICIAL INTELLIGENCE TO IMPROVE FOOD SYSTEM POLICY FRAMEWORKS AND STRATEGIES IN AFRICA

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Abstract. Africa consistently faces policy challenges in all sectors, including its key sector, the food system. Existing challenges intertwine, making policy implementation challenging and necessitating improved regional cooperation and innovative solutions that transcend traditional approaches. This conceptual article examines how AI can be leveraged to enhance Africa's food system policy frameworks and strategies, identifies the challenges of leveraging AI to improve food system policies and strategies, and proposes pathways to strengthen the AI presence in food system adoption and policy-making. The article draws on existing literature as well as personal insights to explore how AI can enhance food systems policy-making in Africa. It reveals that AI holds transformative potential for improving food system policies in Africa by enhancing efficiency, productivity, and resilience across the entire agricultural value chain. By leveraging data-driven insights, AI can help policy-makers and farmers make more informed, timely, and localised decisions. However, poor digital infrastructure, high costs, data gaps, low digital literacy, lack of skilled AI experts, weak regulations, and governance issues, as well as cultural barriers, often combine to create a digital divide, where smallholders are left behind, hindering effective policy implementation and equitable benefits, despite AI's potential for efficiency and sustainability. Efforts should be directed at bridging the digital divide.

Keywords: *Artificial Intelligence, food systems, policies, policy-making, production.*

Rezumat. Africa se confruntă în mod constant cu provocări politice în toate sectoarele, inclusiv în sectorul său cheie, sistemul alimentar. Provocările existente se intersectează, ceea ce face ca implementarea politicilor să fie dificilă și necesită o cooperare regională îmbunătățită și soluții inovatoare care să depășească abordările tradiționale. Acest articol conceptual examinează modul în care IA poate fi valorificată pentru a îmbunătăți cadrele de politici și strategiile sistemului alimentar din Africa, identifică provocările legate de valorificarea IA pentru îmbunătățirea politicilor și strategiilor sistemului alimentar și propune căi pentru consolidarea prezenței IA în adoptarea și elaborarea politicilor sistemului alimentar. Articolul se bazează pe literatura existentă, precum și pe perspective personale, pentru a explora modul în care IA poate îmbunătăți elaborarea politicilor sistemelor alimentare din Africa. Acesta dezvăluie că IA are un potențial transformator pentru îmbunătățirea politicilor sistemului alimentar din Africa prin creșterea eficienței, productivității și rezilienței pe întregul lanț valoric agricol. Prin valorificarea informațiilor bazate pe date, IA poate ajuta factorii de decizie și fermierii să ia decizii mai informate, mai prompte și mai localizate. Cu toate acestea, infrastructura digitală deficitară, costurile ridicate, lacunele în date, nivelul scăzut de alfabetizare digitală, lipsa experților calificați în domeniul inteligenței artificiale, reglementările slabe și problemele de guvernanță, precum și barierele culturale, se combină adesea pentru a crea un decalaj digital, în care micii fermieri sunt lăsați în urmă, împiedicând implementarea eficientă a politicilor și beneficiile echitabile, în ciuda potențialului IA pentru eficiență și sustenabilitate. Eforturile ar trebui să fie îndreptate spre reducerea decalajului digital.

Cuvinte cheie: *Inteligență artificială, sisteme alimentare, politici, elaborare de politici, producție.*

1. Introduction

Artificial Intelligence (AI) is revolutionising society. Its power lies in its capacity to exhibit human cognitive abilities, such as learning, reasoning, and problem-solving, enabling machines to perform complex tasks with extraordinary speed and precision across nearly every industry. AI excels at automating high-volume, repetitive tasks, both digital (such as data entry and email summarisation) and physical (including manufacturing assembly lines and warehouse logistics), thereby freeing humans for more creative and strategic work [1, 2]. AI systems can also process and analyse massive datasets far beyond human capacity, uncovering hidden patterns and generating actionable insights in seconds. This capability is fundamental to improved decision-making and innovation. By providing data-driven insights and predictions, AI enables faster, more reliable, and less biased decision-making in critical fields such as finance and healthcare. Through machine learning (ML) and deep learning (DL), AI models can adapt and improve their performance over time as they are exposed to new data and experiences, becoming more accurate without overt reprogramming. Generative AI, a recent breakthrough, can also create original text, images, code, and music, revolutionising industries like marketing, entertainment, and software development. In addition, AI enables machines to understand and interact using human language (virtual assistants and chatbots) and interpret visual information (facial recognition and autonomous vehicles).

The transformative potential of AI runs across fields and sectors. In the healthcare sector, AI aids in early disease diagnosis (by analysing medical images), accelerates drug discovery, helps personalise treatment plans, and enables remote patient monitoring [3]. In transportation, AI plays a central role in self-driving cars, optimising traffic management, and enhancing navigation apps by processing real-time data to improve safety and efficiency [4]. For the finance sector, AI-powered systems can also detect fraud, perform rapid and accurate credit scoring, manage investments through 'robo-advisers,' and provide personalised banking services [5]. In science and research, AI helps solve complex scientific challenges, from predicting protein structures to modelling climate change effects, by speeding up research and development [1]. In addition, AI-driven chatbots and virtual assistants can also provide instant, around-the-clock support, handling queries and personalising customer experiences [6]. Ultimately, AI is a tool that can augment human capabilities and solve some of the world's most challenging problems. Harnessing this power responsibly, with clear ethical guidelines and a focus on human-centred systems, will be key to ensuring it benefits society as a whole. AI also holds much potential to contribute significantly to policy formulation and implementation. There are currently limited studies that explore the use of AI in this regard. However, this breakthrough will be critical for global regions, such as Africa, which face policy implementation challenges due to poor governance, corruption, weak institutions, infrastructure deficits, and economic dependence on resources, as well as widespread poverty and inequality [7, 8]. African governments are in the early stages of experimentation, but they are facing challenges in adopting widespread use. This article closes this gap by exploring how AI can be used to improve food system policies in Africa. A food system is defined as the entire network of activities and elements involved in food production, processing, distributing, selling, preparing, and disposing, encompassing all activities, from farm to fork (and beyond) and considering its economic, health, social, and environmental impacts [9, 10]. It comprises farmers, processors, retailers, consumers, policies, and the environment, all working together to deliver food, while also facing challenges such as waste, climate change, and ensuring nutrition for all.

African countries have not fully utilised AI in several sectors, including leveraging the technology to address policy issues, despite AI's potential for data analysis, scenario simulation, and real-time monitoring to enhance policy effectiveness. This conceptual article (i) examines how AI can be leveraged to improve Africa's food system policy frameworks and strategies, (ii) identifies challenges of leveraging AI to improve food system policies and strategies, and (iii) proposes pathways to strengthening AI presence in food system adoption and policy-making. The importance of leveraging AI to enhance food system policy is significant, as it provides powerful tools to address the complex, interconnected challenges facing the global food system, including climate change, food security, and sustainability. AI-driven food system policies are crucial for boosting efficiency, sustainability, and security by optimising production, reducing waste, improving supply chains, and enabling better resource management through predictive analytics, precision agriculture, and traceability, helping address challenges like climate change and population growth, while needing careful policy to manage data gaps, equity, and infrastructure. Policy-makers, politicians, and other stakeholders interested in African food systems will find this article informative and engaging.

This article is organised as follows: The following section discusses the components of AI under sub-sections. An outline of the research methodology for the study follows this. Thereafter, the article discusses how AI applications can be leveraged to enhance food systems policies in Africa. It then outlines AI integration challenges and also proposes policy pathways for promoting the integration of AI in food policy design. Lastly, conclusions and recommendations are drawn from the discussion.

2. Components of Artificial Intelligence

The components of AI can generally be grouped into two categories: capabilities that mimic human intelligence and the technologies or subfields used to achieve those capabilities. Table 1 summarises the specific branches of computer science and methods used to build AI systems. The main goal of AI systems is to simulate human intelligence.

Table 1

Components of Artificial Intelligence

Sub-field/Technology	Description	Key Function
Machine Learning (ML)	Algorithms that allow systems to learn patterns and make predictions directly from data. It is the engine of modern AI.	Enables learning and decision-making.
Deep Learning (DL)	A subset of ML that uses deep, multi-layered Artificial Neural Networks (ANNs) to analyse vast amounts of complex data (images, text, audio).	Powers advanced Learning, Computer Vision, and NLP.

Continuation Table 2

Natural Language Processing (NLP)	Focuses on the interaction between computers and human language, allowing machines to read, understand, and generate text or speech.	Enables language understanding.
Computer Vision (CV)	Equips machines to 'see' and interpret visual data from images or videos, enabling tasks such as object recognition, facial recognition, and image classification.	Enables perception (specifically visual).
Robotics	The integration of AI with physical machines, allowing robots to perceive their environment, plan movements, and execute tasks autonomously.	Integrates AI for physical action and perception.
Expert Systems	AI programmes are designed to mimic the decision-making of a human expert in a specific domain, using a knowledge base and a set of inference rules.	Supports specialised reasoning and problem-solving.
Generative AI	A recent branch focused on creating new, original content (text, images, code, video) rather than just analysing existing data.	Enables new forms of language understanding and creation.

Source: Authors

2.1. Machine Learning

ML is a subset of AI that focuses on developing statistical algorithms (models) that enable computer systems to learn from data and make predictions or classifications without being explicitly programmed for the specific task [11]. When an ML model is fed a large amount of data, it can learn the underlying patterns and relationships within that data, enabling it to perform the task effectively. Its performance improves progressively with more 'experience' (data) [2].

The general process of machine learning typically involves several phases, including data pre-processing. This is when raw data is cleaned, transformed, and prepared to be suitable for the algorithm (e.g., handling missing values, normalising data). The pre-processed data is used to train the algorithm (Training the Model). The algorithm iteratively adjusts its internal parameters to find a mathematical relationship that minimises the difference between its predictions and the actual known outcomes in the training data. A separate dataset is used to check if the model can accurately generalise its learning to new, unseen data (Evaluating the Model). The model is then refined further to improve its accuracy and efficiency (Optimisation).

ML systems are generally categorised into four main types based on how they learn:

- *Supervised Learning*: The model is trained on labelled data (input data paired with the correct output/answer). The goal is to map an input to a known output and make predictions. This system can classify (categorise data, such as identifying a picture) and perform regression (predict a numerical value).
- *Unsupervised Learning*: This model is trained on unlabelled data. The goal is to identify meaningful patterns, structures, and groupings within the data without relying on external information. Common tasks include clustering (grouping similar data points and association (discerning correlations).
- *Reinforcement Learning:* An ‘agent’ learns by interacting with an environment through a trial-and-error process. The goal is to find the best sequence of actions to maximise

a cumulative reward (positive reinforcement) and minimise penalties (negative reinforcement). This includes training robots to perform tasks and developing AI to solve complex issues.
- *Generative AI*: This focuses on creating new content (text, images, audio, video) that resembles the patterns learned from the existing training data.

ML powers many technologies, including recommendation engines, fraud detection, predictive maintenance, autonomous vehicles, and translation apps and chatbots [12, 13].

ML profoundly impacts society by automating tasks, boosting efficiency, and enabling data-driven decisions across industries. In food systems, ML boosts efficiency, sustainability, and safety from farm to fork, enabling precision agriculture, optimising supply chains to cut waste, automating quality control, predicting demand for better inventory, and even creating personalised nutrition, though ethical concerns about data access and cost remain [14, 15]. By analysing vast datasets from sensors, images, and the Internet of Things (IoT) devices, ML helps farmers manage resources more effectively, processors ensure quality, and businesses tailor products, resulting in significant cost savings and environmental benefits [16, 17]. In essence, ML offers powerful tools to build a more resilient, efficient, and sustainable food system by making data-driven decisions across all stages; however, ethical deployment and broad accessibility remain crucial for realising its full potential.

2.2. Deep Learning

DL is a highly effective subset of ML that utilises artificial neural networks with multiple layers to learn complex patterns directly from large datasets [18]. It is inspired by the structure and function of the human brain's neural circuits [19]. The key component of DL is the deep neural network (DNN). Unlike traditional ML, DL models can automatically discover and learn the relevant features directly from the raw data, eliminating the need for manual, human-guided feature extraction [18]. DL performance generally continues to improve as the volume of data increases, which is crucial in the age of big data. It excels at tasks involving unstructured data such as images, audio, and text [20]. Table 2 summarises common DL architectures. DL is the backbone of many modern AI technologies, including CV and NLP.

Table 3

Common Deep Learning Architectures

Architecture	**Primary Use Case**	**Key Mechanism**
Feedforward Neural Networks (FNN)	Simple classification and regression tasks.	Information flows in one direction from input to output.
Convolutional Neural Networks (CNN)	Image and video processing (Computer Vision).	Utilises convolutional layers to automatically extract spatial features, such as edges and patterns.
Recurrent Neural Networks (RNN)	Sequential data (time series, text).	Nodes have "memory" to retain information from previous steps in the sequence.
Transformers	Natural Language Processing (NLP) and Large Language Models (LLMs).	Utilises an attention mechanism to prioritise the significance of various parts of the input data.

Source: Authors

DL can revolutionise food systems by boosting precision agriculture (yield prediction, pest/disease ID, smart irrigation), optimising the supply chain (waste reduction, traceability, quality control, fraud detection), and improving food safety and nutrition (contaminant detection, personalised diet). Benefits include increased efficiency, reduced environmental impact, enhanced food security, and greater sustainability through better resource management and predictive insights across the entire food chain.

2.3. Natural Language Processing

NLP is a subfield of AI, computer science, and computational linguistics that focuses on enabling computers to interpret, manipulate, and comprehend human language, both spoken and written [21]. Its ultimate goal is to bridge the communication gap between humans and machines, allowing people to interact with technology using natural language in daily activities. NLP models, often based on ML and DL, process human language by breaking it down and analysing its structure and meaning. The process typically involves several core techniques, such as breaking down text into individual units (tokens), such as words, phrases, or symbols and simplifying words to their root form to reduce vocabulary size and allow the computer to treat different forms of a word (such as ‘running,’ ‘ran,’ ‘runs’) as the same base word (‘run’). In addition, NLP can identify the grammatical role of each word (such as noun, verb, or adjective) to understand how words relate to each other. It can analyse the grammatical structure of a sentence to ensure it is structurally sound and can extract relationships between words [23]. It can also determine the meaning of the language, encompassing the individual word meanings and the overall meaning of the sentence.

NLP is an integral part of many modern technologies and workflows. It is generally divided into two main branches, namely, Natural Language Understanding (NLU) and Natural Language Generation (NLG) (see Table 3).

Table 4

Branches of Natural Language Processing

Branch	**Focus**	**Example Applications**
NLU (Understanding)	Parsing text or speech to understand what is being said (intent, sentiment).	Sentiment Analysis (analysing reviews), Entity Recognition, Key-Phrase Extraction.
NLG (Generation)	Generating new, coherent, and meaningful text or speech as a response.	Chatbots, Machine Translation, Text Summarisation, Large Language Models (LLMs).

Source: Authors

The common real-world examples of NLP include Siri, Alexa, and Google Assistant, which use NLP for speech recognition and command interpretation. Tools like Google Translate utilise NLP to translate text between languages. It is also used in sentiment analysis by businesses to gauge public opinion from social media, customer reviews, or surveys. Chatbots also rely heavily on NLP for understanding queries and generating responses. In addition, NLP helps search engines to understand the intent behind the query, not just matching keywords.

In food systems, NLP can help unlock insights from text data to inform better decisions, automate tasks such as quality control and customer service, enhance food safety through compliance monitoring, personalise nutrition, optimise supply chains, and improve food security by analysing public discourse and policy. It helps analyse consumer feedback, manage food donations, identify dietary trends, and create efficient, data-driven food management systems from farm to table.

2.4. Computer Vision

CV is a field of AI that focuses on enabling computers to perceive, interpret, and comprehend visual data from the world, much like humans use their eyes and brains [25]. Essentially, CV teaches machines to extract meaningful information from digital images, videos, and other visual inputs and then make decisions or take action based on that information. CV systems typically rely on ML and DL models, especially Convolutional Neural Networks (CNNs), which are trained on massive amounts of visual data [26]. The general process involves a few core steps, such as capturing visual data using devices like cameras, sensors, or scanners, and cleaning and enhancing the raw data (e.g., resizing, adjusting brightness, reducing noise). Algorithms process the data to detect and recognise patterns by comparing them against an extensive database of known patterns. The system then identifies patterns (like objects or faces) and outputs information or triggers an action.

CV performs a range of tasks to interpret visual data, including image classification. It can assign a single label or category to an entire image. It can also identify and locate multiple objects within an image, typically by drawing a bounding box around each one and providing a label (e.g., locating all cars and pedestrians in a street scene). In addition, CV can monitor the movement of one or more objects across a sequence of video frames over time. It can also convert printed or handwritten text within an image into editable digital text. The CV technology has a wide range of real-world applications across various industries (see Table 4).

Table 5

Computer Vision Real-World Application

Industry	**Example Application**
Automotive	Autonomous vehicles (detecting pedestrians, traffic signs, and lanes).
Healthcare	Analysing medical images (X-rays, MRIs) to detect diseases like tumours or abnormalities.
Security/Surveillance	Facial recognition for identification and monitoring public spaces.
Manufacturing	Quality control by detecting defects on a production line in real-time.
Retail/E-commerce	Visual search, inventory management, and analysing customer behaviour.

Source: Authors

CV revolutionises food systems by boosting efficiency, safety, and sustainability from farm to fork, enabling automated crop monitoring for precise resource use, real-time quality control in processing to detect defects and contamination, accurate yield prediction, waste reduction through better logistics, and enhanced traceability for regulatory compliance and consumer trust, making the entire food chain smarter and less wasteful.

2.5. Robotics

Robotics is an interdisciplinary branch of engineering and computer science that involves the design, construction, operation, and use of robots, machines programmed to perform tasks traditionally done by humans [27]. The primary goal of robotics is to develop intelligent machines that can assist humans in various ways, particularly in tasks that are repetitive, hazardous, or require precise execution [28, 29].

Regardless of its complexity or level of autonomy, every robot system consists of three fundamental components, namely, mechanical construction. This is the physical body of the robot, comprising the frame, motors (also known as actuators), and manipulators (such as arms or wheels). It is designed to achieve a specific task and address the physics of its environment. It also includes electrical components. These are the power and sensory systems of the robot. This includes the power source (such as a battery), the electrical circuits, and the sensors that enable the robot to perceive its environment (e.g., cameras, touch sensors, and GPS). In addition, it includes software or programming. This is the 'brain' that dictates how the robot operates. Programs determine when and how a robot moves, processes sensor data, and makes decisions. Robotics software can range from simple remote control to advanced AI, allowing the robot to operate autonomously and learn from its environment. Robotics is a highly collaborative field that draws knowledge from several key disciplines, including mechanical and electrical engineering. Robots are deployed across a wide range of industries to enhance productivity, efficiency, and safety (Table 5).

Table 6

Examples of fields where robotics is used

Industry	Examples of Robotic Use
Manufacturing	Industrial Robots perform assembly, welding, painting, and quality control, especially in the automotive and electronics sectors.
Healthcare	Surgical Robots (like the da Vinci system) perform minimally invasive procedures with high precision. Rehabilitation Robots (exoskeletons) assist patients in regaining mobility.
Logistics & Warehousing	Autonomous Mobile Robots (AMRs) manage inventory, transport goods, and automate order fulfilment and packaging.
Exploration	Space Probes and Rovers (like the Mars rovers) explore dangerous or remote environments. Underwater Robots explore the deep sea.
Agriculture (Agri-Robotics)	Autonomous systems perform planting, harvesting, weed management, and collect crop health data (often using UAVs/drones).
Consumer/Service	Robotic vacuum cleaners, social robots for elderly care or education, and automated food preparation systems.

Source: Authors

In food systems, robotics boosts efficiency, safety, and quality by automating tasks like harvesting, processing, and packaging, reducing labour costs and human error, while improving consistency and traceability from farm to table, leading to less waste, better resource use (precision agriculture), and enhanced food safety through consistent handling and real-time monitoring, creating a more resilient and sustainable food supply chain.

2.6. Expert Systems

An Expert System is a computer programme, a subset of AI, that emulates the decision-making ability of a human expert in a specific, specialised domain [30]. Instead of using conventional procedural programming, they solve complex problems by reasoning through a body of knowledge, often represented as 'if-then' statements, some statements that define relationships and guide decision-making [31]. The effectiveness of an expert system relies on its main components working together. These are the knowledge base, the core of the system, containing domain-specific facts, rules, and heuristics (rules of thumb) gathered from human experts. The quality and completeness of the knowledge base are critical to the system's performance [30]. The other component is the inference engine. This is the reasoning component. It applies logical rules to the knowledge base to derive conclusions, recommendations, or new facts. It typically uses methods like forward chaining (begins with known facts and applies rules to infer new facts until a goal is reached (data-driven) and backward chaining (begins with a goal (hypothesis) and works backward to find the facts and rules that support that goal (goal-driven) [32]. Another component is the user interface. This is the system's communication bridge, allowing users (who are often non-experts) to input queries and receive and understand the system's advice or diagnosis [30].

Expert systems have been successfully applied across diverse fields, including healthcare, where they aid in diagnosis and treatment planning, and finance, where they are utilised for fraud detection, credit risk assessment, and investment analysis. The use of expert systems offers several advantages. They capture human knowledge, preventing its loss when an expert retires or leaves [32]. They provide consistent and unbiased recommendations based on established rules, make expert-level knowledge available quickly to non-experts across various locations, and can justify their conclusions, which is important for critical applications such as medical diagnosis.

Expert systems offer numerous benefits across the entire food system, primarily by replicating human expertise to provide consistent, data-driven decision support, which leads to improved efficiency, enhanced sustainability, and greater food safety and quality [33].

2.7. Generative Artificial Intelligence

Generative Artificial Intelligence (Generative AI) is a powerful subfield of AI that focuses on creating new content and ideas [34]. Unlike traditional AI, which may analyse existing data for insights or predictions, Generative AI utilises ML models to generate novel and realistic text, images, code, and other forms of data [35].

Generative AI is powered by large and complex machine learning models, often based on neural networks and DL. The core process involves training on massive datasets. In this regard, the model is fed vast amounts of existing content. During training, the model identifies the underlying patterns, relationships, and structures of the data. For instance, a language model learns grammar, syntax, and how words relate to each other. When given a prompt (an input or request), the model uses the patterns it learned to predict and produce the most statistically likely or coherent next piece of data, whether it is the next word in a sentence, the next pixel in an image, or the next note in a song [36].

The key types of models include Large Language Models (LLMs). Like the GPT series, this model is focused on language-based tasks such as text generation, conversation, and summarisation. The other model is Generative Adversarial Networks (GANs). This consists of two competing neural networks (a Generator and a Discriminator) that work together to produce increasingly realistic output. Another key model is diffusion models. This class of models generates new data by iteratively removing noise from an initial random input [37].

Generative AI is revolutionising food systems by creating new recipes, personalised nutrition plans, and marketing content, while also optimising farming (disease detection, yield prediction) and supply chains (demand forecasting, waste reduction) [38]. It serves as a powerful tool for innovation, sustainability, and efficiency, enabling data-driven decisions from farm to table, generating novel products, and enhancing consumer engagement through hyper-personalisation. However, ethical considerations surrounding data and bias remain crucial [39].

Considering the revolutionary role that AI is playing in various fields, including food systems, it is also vital to explore how it can be utilised to enhance policy formulation and implementation, a significant challenge for most African countries.

3. Materials and Methods

This article adopts a conceptual research methodology. This is not only because AI solutions are still evolving, but also because their adoption and integration in Africa's food systems are still in their early stages. The article uses current abstract ideas about AI solutions and existing literature on AI integration in food systems to examine how these solutions can be leveraged to improve food systems policy frameworks and strategies. In utilising this methodology, the authors first defined the concept of food systems, drawing from reputable policy and research networks including the HLPE and the FSNet Africa. The authors then identified the types of AI solutions and their applications in various activities across the food system chain. It then explored how such AI solutions can be utilised to inform policy frameworks and strategies, as well as improve food systems in the African context.

Underpinned by this conceptual approach, the article draws from both grey and academic literature on AI-driven solutions. The synthesis of these texts was then combined with personal abstraction. The argument was that not all problems can be resolved by empirical evidence. Instead, abstraction provides a valuable tool for making comments when empirical evidence is not yet available. This methodology provided a clear roadmap, defining key variables and guiding the entire study from design to analysis, ensuring focus and consistency in analysis, especially because very few studies explore how AI can be used in policy formulation. The methodology also clarified the study's context, justified the research, and helped identify gaps, leading to more structured arguments and propositions on the possibilities of integrating AI in policy formation.

The conceptual research methodology, however, is not without limitations. These include the lack of empirical grounding, reliance on existing literature, difficulty in proving causality, and challenges in demonstrating validity and reliability without data, making findings harder to generalise or verify compared to empirical studies. Nonetheless, this article effectively highlights key instances where AI solutions can be leveraged to design food systems policies and strategies. It is hoped that future studies will build on the arguments presented here, using empirical evidence to ground them more firmly.

4. AI Applications for Enhancing Food Systems Policy Frameworks and Strategies

Africa's policy formulation and implementation face significant hurdles, including weak governance, corruption, political interference, poor stakeholder engagement, and a gap between policy goals and local realities, which often lead to policy failures despite good intentions. This is evident in stalled development goals and inconsistent service delivery. These issues stem from a disconnect between conceptual policy design and on-the-ground realities, often resulting in unrealistic policies, a lack of local buy-in, or being derailed by political interests. This review revealed that AI offers transformative potential to enhance food system policy frameworks and strategies in Africa by providing data-driven insights, improving efficiency, and fostering resilience throughout the entire value chain.

4.1. Climate and Disaster Resilience Policy

AI solutions can be leveraged to both formulate and implement climate and disaster resilience policies in African countries. For instance, AI-driven predictive analytics can be crucial for developing policies that mitigate the impacts of climate change. This can be achieved by using AI solutions to analyse satellite imagery, historical weather data, and real-time sensor information to provide accurate, localised weather forecasts and predictive alerts for droughts, floods, and pest/disease outbreaks (like locust invasions). This data can enable governments to implement preemptive policies, such as adjusting planting calendars, coordinating the distribution of drought-resistant seeds, and launching early disaster response efforts. India is one of the best examples of countries where AI directly influences farmers' decisions, which are then scaled up into policy recommendations for the national agricultural strategy. In India, Microsoft's AI Sowing App uses ML to compare 30 years of historical climate data with real-time weather. It advises farmers (*via* SMS) on the optimal time to sow crops, leading to a reported 30% increase in productivity per hectare [40]. This model directly informs best practices for agricultural extension services and resource management.

In the United States (US), AI is being used primarily to enhance efficiency, food safety, and compliance with federal programmes. In the School Nutrition Programme Management, the US utilises AI to assist school districts in managing, reporting on, and maintaining compliance with the US Department of Agriculture's (USDA) Nutrition Standards for School Meals [41, 42]. By automating data extraction and reporting, AI influences the efficiency and integrity of national food assistance programmes. The US agriculture also heavily utilises AI-driven precision farming, which involves using satellite data, drones, and sensors to optimise planting, water, and fertiliser use. This data-driven efficiency can inform policies related to resource conservation, sustainability, and climate-smart agriculture. Reliable yield data can also inform national food reserve policies, import/export decisions, and resource allocation (e.g., fertiliser subsidies).

Several African countries are already integrating AI solutions, primarily to address logistical issues and enhance the resilience of smallholder farmers, a key focus for food security policy. Companies such as Twiga Foods in Kenya use AI-driven logistics to connect small farmers directly with urban retailers [43]. By optimising supply routes and predicting market demand, they reduced post-harvest losses from 30% to just 4% [43]. Policy can be influenced by demonstrating how technology can streamline national food distribution and reduce waste. Additionally, AI-powered smartphone apps in countries such as Uganda, Tanzania, and South Africa utilise computer vision to diagnose plant diseases from leaf images [16]. By enabling early corrective measures, this technology has improved crop resilience and significantly reduced yield losses, informing national plant health and protection strategies. In Malawi, AI is being applied to improve early warning systems for humanitarian aid and policy intervention [44]. An ML approach in southern Malawi was developed to infer predictors of food insecurity and forecast household-level outcomes up to four months in advance with high accuracy [45]. This directly informs and strengthens government and humanitarian early warning systems for timely intervention in food-insecure regions. This data is critical for policy-makers to address drought preparedness and resource allocation.

AI-powered mobile apps deliver timely, context-specific agronomic advice (e.g., optimal planting/harvesting times, irrigation needs) directly to smallholder farmers in several countries [16]. The data and insights generated by these AI tools can, therefore, be used to inform policies that ensure that farmers and other food system stakeholders have access to the knowledge to adapt to climate volatility, leading to more stable food production.

4.2. Enhancing Supply Chain and Market Efficiency

AI can optimise the movement of food, from farm to consumer, reducing waste and strengthening market mechanisms, which can then be regulated and supported by policies. AI algorithms can predict demand and optimise transportation routes to minimise post-harvest losses (a major challenge in Africa) and improve the efficiency of food distribution, especially from rural to urban centres. AI-driven insights can inform policies for infrastructure investment and logistical protocols. These can include predictive policies designed to reduce losses. In this regard, ML algorithms analyse data from IoT sensors on transport vehicles and storage facilities (temperature, humidity, time), combined with data on product type, external weather, and route conditions. This enables policymakers to pinpoint the specific geographic 'hotspots' or 'pinch points' where losses are highest. Policies can then be targeted, focusing investments on building new cold chain infrastructure along those routes, providing subsidies for smart storage facilities, or implementing mandatory quality control checkpoints informed by AI risk scoring.

AI-driven insights can also be used to develop policies and strategies that optimise route and inventory. In this regard, AI routing software can be used to dynamically process real-time traffic, weather, and market demand to find the most fuel-efficient and fastest delivery paths. Policy can incentivise the use of these platforms (e.g., through tax breaks for certified logistics tech adoption) and mandate data sharing for logistics providers to improve overall network flow, ensuring perishable goods reach markets efficiently, thereby reducing spoilage and emissions.

AI solutions can be used to improve market price transparency and stability. Market volatility and information asymmetry often disadvantage smallholder farmers. AI can inform policies that create a fairer, more transparent marketplace. DL models (such as CNNs) analyse historical prices, production volumes, weather patterns, global trade data, and consumer trends (including social media sentiment) to predict future commodity prices with high accuracy. This data can enable the development of policies that stabilise farmer income. African governments can establish data-driven minimum support prices or futures contracts informed by forecasts, thereby protecting farmers from sudden price fluctuations. The data can also be used to design policies that regulate market interventions. Policy can establish rules for when and where governments should release strategic grain reserves or introduce subsidies to cool down or stabilise prices.

AI solutions can also be used to ensure transparent digital marketplaces. AI-powered digital platforms can connect farmers directly with buyers, removing exploitative intermediaries. AI algorithms can instantly verify product quality (*via* CV) and automatically suggest the fairest price based on real-time market data. African governments can enact mandates or incentives for the use of such platforms, increasing market access for smallholders and ensuring transparency in transactions, which is crucial for reducing corruption and guaranteeing fair trade.

Several African countries like Kenya, Nigeria, South Africa, Zimbabwe, and Ghana are leveraging AI in agriculture to boost food supply chains and market efficiency, using solutions for smart farming (Apollo Agriculture in Kenya, Zenvus in Nigeria), crop disease diagnosis (PlantVillage Nuru app), supply chain logistics (Twiga Foods in Kenya), predictive spoilage in storage (Zimbabwe's AI silos), and precision agriculture *via* drones (Aerobotics in South Africa) [14, 46]. These technologies reduce losses, improve yields, cut costs, and enhance market access for smallholder farmers [4413]. Improved logistics help reduce post-harvest losses (a major policy concern), while better traceability aids in enforcing food safety standards and tackling illegal trade. Therefore, African countries can utilise these insights to design policies and strategies that further enhance their systems.

4.3. Improving Resource Management and Sustainability

Africa's food systems face central resource management and sustainability hurdles, primarily driven by climate change (droughts, floods), poor infrastructure, land degradation, food loss (post-harvest), poverty, limited technology adoption (irrigation, seeds), and reliance on rain-fed agriculture, all straining water, soil, and food security for a growing population [41, 45]. Addressing these challenges requires sustainable practices, improved inputs, better infrastructure, and policy support for resilient and inclusive food systems. Resource management and sustainability are vital for Africa's food systems to ensure food security, boost economic growth, combat climate change, and achieve social equity by improving soil health, water efficiency, biodiversity, and empowering smallholder farmers, preventing resource depletion, and building resilience against climate shocks, which is critical given Africa's growing population and environmental pressures [46].

AI can be leveraged to support policies aimed at the sustainable and efficient use of finite resources, which are critical for long-term food system resilience. African governments can enact policies and incentives that promote AI-driven precision farming. AI tools, often accessible *via* mobile apps, provide hyper-localised recommendations on when and how much to water or apply fertiliser, reducing input costs for farmers and minimising environmental run-off [45]. AI-powered mobile apps can also help farmers instantly diagnose crop diseases and pests from photos, providing treatment recommendations. This supports sustainability policies by optimising the use of scarce resources, reducing costs for farmers, and lowering environmental impacts. Policies can promote these tools to reduce crop losses, minimise the reliance on broad-spectrum pesticides, and ensure food safety through rapid diagnosis.

Africa has been a primary testing ground for AI in agriculture due to the high density of smallholder farmers and the threat of regional crop failures. Countries such as Kenya, Tanzania, and Ethiopia have extensively utilised PlantVillage Nuru, an AI assistant developed by Penn State University in collaboration with the FAO, to identify diseases like Brown Streak and Mosaic Virus in crops like cassava, potatoes, and maise (Consultative Group on International Agricultural Research [48]. In Kenya, it was also used to track desert locust outbreaks. In the Democratic Republic of Congo and Benin, the Tumaini app is used, specifically designed for banana farmer [48]. The app can detect six major banana diseases and pests with over 90% accuracy by analysing photos of any part of the plant (leaf, fruit, or trunk) [49]. In Cameroon, local farmers utilise AI-powered apps that provide offline functionality, enabling them to upload photos in remote areas with limited internet connectivity and receive instant treatment advice [50]. In Nigeria and the Ivory Coast, AI is used to monitor the health of cassava and cocoa, often integrated with satellite data to track the spread of the 'swollen shoot' virus (Global System for Mobile Communications Association [51].

African policy frameworks and strategies can promote the development and scaling of these AI tools to curb the massive crop losses that currently undermine food security on the continent.

4.4. Policy for Enhanced Traceability and Food Safety

AI, often combined with blockchain technology, can create policy frameworks that guarantee the safety and provenance of food by providing real-time traceability systems. AI systems can aggregate data from IoT sensors, farm records, and processing logs, linking this information to an immutable blockchain ledger. This creates an end-to-end digital record of a product's journey from farm to fork. Policies can mandate these transparent traceability standards for high-value or exported goods. In the event of a food safety issue, AI can isolate the contaminated batch and identify the source within seconds [52], allowing for rapid, targeted recalls rather than widespread disruptions.

AI-driven solutions can also provide automated quality control across the food chain. CV and ML are used in processing facilities to automatically inspect, sort, and grade produce based on size, colour, and defect identification, ensuring consistency and safety [13]. Policy can incentivise the adoption of these automated sorting systems to meet international quality and safety standards, which is vital for accessing profitable export markets. AI moves policy from relying on outdated, slow-moving surveys to using real-time, granular data. This ensures policy interventions are effective, financially viable, and directly address bottlenecks in the supply chain and market system.

4.5. Financial Strategies and Agri-Finance Enhancement

AI and ML are key to de-risking and expanding access to financial services. Traditional financial institutions often lack data on smallholder farmers [15]. AI can utilise alternative data sources, such as satellite images of farm health, mobile money transactions, and historical crop yields, to create more accurate credit risk profiles. This enables financial institutions to offer tailored microfinance and small loans to farmers who were previously considered unbankable, thereby boosting investment in their farms. AI can be used for credit scoring among smallholder farmers, utilising non-traditional data sources (e.g., mobile money transactions, satellite imagery of farm health). Policies supporting these models expand access to finance and insurance, enabling farmers to invest in productivity-enhancing tools and technologies. Policies that support financial access for African smallholder farmers are crucial for boosting food security, reducing poverty, and promoting sustainable development by enabling investment in modern inputs, technology, and resilience. This, in turn, fosters economic growth and creates a more inclusive agricultural system through measures such as credit guarantees, digital identity, and tailored financial products.

Several African countries are developing national AI strategies that either directly mention agriculture as a key application area or support AI-driven initiatives (often *via* public-private partnerships), which, in turn, facilitate farmer access to finance. Countries with policies or significant government-backed initiatives influenced by AI to improve financial access by farmers include Kenya. The government supports a thriving agri-fintech scene. The Central Bank of Kenya has implemented policies to facilitate mobile money transactions, which are crucial for digital payments in the agricultural sector. Government entities also collaborate with private firms, such as Apollo Agriculture and FarmDrive, which utilise AI and ML to develop alternative credit scoring models for smallholder farmers who lack traditional collateral [53]. Likewise, Rwanda has a National AI Policy in development and has also implemented the Smart Nkunganire System (SNS), a digital platform that uses data on soil conditions and weather patterns to streamline input distribution. This system supports e-farmer IDs and cooperative registries, which enable farmer groups to access pooled loans and insurance products supported by the government. In Ethiopia, the government has launched the Digital Agriculture Roadmap (DAR) 2032, which aims to improve farmers' access to financial services through digital tools. State banks and private partners (such as the Cooperative Bank of Oromia) are piloting digital lending platforms that integrate satellite imagery and mobile data to fast-track loan approvals.

In West Africa, several countries are integrating AI to enhance financial access for smallholder farmers. For instance, Ghana has a National AI strategy (launched in 2022) and an emphasis on digital agriculture. The Development Bank of Ghana (DBG) is partnering with organisations to pilot AI-driven chatbots for agricultural guidance and provide authoritative data for hyper-specific farming advice. The government also supports the Ghana Incentive-Based Risk Sharing System for Agricultural Lending (GIRSAL), which incentivises banks to lend to the agricultural sector, leveraging digital platforms and warehouse receipts. In Nigeria, the government supports private sector-led initiatives. Fintech companies such as ThriveAgric and Farmcrowdy utilise predictive data to assess risk and extend credit, a model that benefits from a supportive regulatory tone set by the central bank, which enables digital IDs and flexible collateral laws.

In Zambia, agritech companies such as Apollo Agriculture leverage AI to assess creditworthiness and prevent fraud in farmer lending programmes, operating within a policy environment that is becoming increasingly conducive to digital agriculture solutions. These countries demonstrate a growing recognition of the role AI can play in overcoming traditional barriers to agricultural finance in Africa. However, many are still in the early stages of implementing their policies.

4.6. Addressing Policy Challenges and Promoting Inclusivity

Africa’s food systems are widely documented as facing major policy and inclusivity challenges, including marginalisation of women, youth, and smallholder farmers; limited access to resources, finance, and technology; weak infrastructure (energy, transport, storage); power imbalances favouring large corporations; and climate change impacts worsening existing inequalities, all leading to persistent hunger, malnutrition, and unequal economic opportunities despite agriculture’s importance [42, 54].

AI can help address systemic policy challenges related to equity and governance. For instance, ML can be used to analyse socio-economic and farming data to improve the targeting of government subsidies and financial aid (such as fertiliser and seeds) to ensure they reach the intended smallholder farmers, youth, and women, reducing leakage and inefficiency [42, 55]. AI can promote inclusive African food systems by empowering smallholders with tailored advice, boosting access to finance, optimising supply chains for equity, and improving sustainability through data-driven insights, all while requiring supportive policies, ethical data use, and a focus on local languages to ensure technology serves marginalised groups like women and youth, aligning with Africa’s development goals [56]. In addition, since AI relies on vast amounts of data, policy must focus on establishing clear data governance frameworks. This includes regulations on data ownership, privacy, ethics, and ensuring that AI models are trained on diverse, localised data to avoid bias against indigenous crops, soil types, or marginalised communities.

5. Challenges to AI Implementation and Policy Gaps

For AI to truly transform food systems in Africa, several structural challenges must be addressed through targeted policy and investment. Table 6 summarises the AI implementation and policy gaps in Africa's food systems.

Table 7

AI Implementation and Policy Gaps in Africa's Food Systems

Challenge	**Policy / Investment Gap**
Data Gaps	Lack of localised, high-quality data on indigenous crops, soil types, and local climates. Most AI models rely on foreign training data.
Digital Infrastructure	Low internet connectivity in rural areas and a lack of reliable, affordable computing power.
Digital Skills Divide	Many smallholder farmers and extension workers lack the basic digital literacy needed to use AI-powered apps and services effectively.
Cost and Access	High cost of AI-enabled hardware (drones, sensors) and software, creating a digital divide between commercial farms and smallholders.
Governance and Ethics	Lack of clear policy frameworks concerning data ownership, privacy, ethical use, and algorithmic bias. AI must empower, not marginalise, smallholder farmers.

Source: Authors

To successfully harness AI in Africa's food systems, African policymakers must focus on creating an inclusive and enabling environment, emphasising connectivity, compute, context, and competency. To invest in connectivity and computing, governments must prioritise public-private partnerships to expand low-cost rural internet infrastructure and shared computing resources. This will make AI accessible to Africa's farmers, most of whom are smallholder farmers and peasants. African policy-makers also need to promote data localisation and governance [57]. This can be achieved by developing national and regional open data policies and incentives for collecting and sharing high-quality, localised agricultural data and by establishing clear ethical guidelines and data privacy regulations. In addition, African countries need to ensure the context and affordability of AI solutions. This requires AI solutions to be multilingual, user-friendly, and designed specifically for the needs of smallholder farmers and local crops. This should be supported by subsidies for low-cost, smartphone-based tools. African countries also need to build competency and capacity. This can be achieved by integrating digital literacy and AI-use training into agricultural extension programmes and farmer field schools.

6. Conclusion

AI is revolutionising the world, including the food system sector. AI is being integrated to address a range of issues in the food system. This article speculated on how AI can be used to improve food system policies and strategies in Africa. Africa's key policy challenges involve overcoming poor governance, corruption, and weak institutions; addressing massive infrastructure deficits and economic dependence on resources; and tackling widespread poverty and inequality. These issues intertwine, making policy implementation challenging and necessitating improved regional cooperation and innovative solutions that transcend traditional approaches. The article revealed that AI holds transformative potential for improving food system policies in Africa by enhancing efficiency, productivity, and resilience across the entire agricultural value chain. By leveraging data-driven insights, AI can help policy-makers and farmers make more informed, timely, and localised decisions. However, poor digital infrastructure, high costs, data gaps, low digital literacy, lack of skilled AI experts, weak regulations, and governance issues, as well as cultural barriers, often combine to create a digital divide, where smallholders are left behind, hindering effective policy implementation and equitable benefits, despite AI's potential for efficiency and sustainability. The article also proposed some policy directions to bridge the digital divide within Africa's food systems.

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