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Review

The Application of Artificial Intelligence Models for Food Security: A Review

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Abstract: Emerging technologies associated with Artificial Intelligence (AI) have enabled improvements in global food security situations. However, there is a limited understanding regarding the extent to which stakeholders are involved in AI modelling research for food security purposes. This study systematically reviews the existing literature to bridge the knowledge gap in AI and food security, focusing on software modelling perspectives. The study found the application of AI models to examine various indicators of food security across six continents, with most studies conducted in sub-Saharan Africa. While research organisations conducting AI modelling were predominantly based in Europe or the Americas, their study communities were in the Global South. External funders also supported AI modelling research on food security through international universities and research institutes, although some collaborations with local organisations and external partners were identified. The analysis revealed three patterns in the application of AI models for food security research: (1) the exclusive utilisation of AI models to assess food security situations, (2) stakeholder involvement in some aspects of the AI modelling process, and (3) stakeholder involvement in AI modelling for food security through an iterative process. Overall, studies on AI models for food security were primarily experimental and lacked real-life implementation of the results with stakeholders. Consequently, this study concluded that research on AI, which incorporates feedback and/or the implementation of research outcomes for stakeholders, can contribute to learning and enhance the validity of the models in addressing food security challenges.

Keywords: Artificial Intelligence; food security; machine learning; Global South; funding

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1. Background

The pursuit of a sustainable food system has prompted the adoption of innovative technologies like Artificial Intelligence (AI) to enhance food security. Artificial Intelligence (AI) encompasses a wide range of disciplines within computer science, with the aim of constructing intelligent machines capable of executing tasks typically demanding human intelligence [1]. AI has become imperative due to the uncertainties associated with the intricate and dynamic relationship among social, economic, and environmental factors that underlie food security [2,3]. For instance, a report by the FAO, IFAD, UNICEF, WFP, and WHO [4] indicates that global food insecurity is projected to worsen due to rapid population growth, overexploitation, the depletion of natural resources, and unprecedented climate change. About 70% more food will be needed by 2050 to feed the growing population, while the global food consumption in calories from the use of agricultural commodities is projected to increase by 1.3% per year over the next decade [5]. Food for developing countries is produced by 80% of smallholder farmers who rely on simple technologies [6]. The rise in agricultural input prices experienced over the last two years, particularly the rising fertiliser costs, can lead to higher food prices, and this raises concern about global food security [7]. Stakeholders in the food and agricultural sector face the challenge of optimising their operations to minimise losses and costs while maximising yields. This challenge encompasses factors, such as low crop yields, losses due to weather events (e.g., droughts, floods, and frost), pest and disease incidences, post-harvest losses during storage and transportation, high costs of production, low revenue generation, and uncertainties due to market dynamics among other issues [8].

In the context of the numerous challenges affecting stakeholders' efforts of ensuring food security, AI appears to be a tool that can help develop comprehensive food security management strategies, optimising crop yields, minimising losses, and reducing operational costs [9]. AI models offer significant advantages for food security purposes in terms of efficiency, accuracy, consistency, automation, pattern recognition, availability, and scalability, but they also come with challenges related to data, cost, ethics, and the need for ongoing management [10]. The choice between traditional methods and AI models depends on the specific problem, available resources, and the trade-offs involved. AI comprise analytical tools, such as data analytics, machine learning, and optimisation models, which can be applied to historical data and real-time information to make informed decisions [11]. This study focuses on the application of AI models. AI modelling is the key to building automated, intelligent, and smart systems ensuring that processes are better, faster, and more precise [12]. A combination of numerical optimisation, risk analyses, parameterization and scenario planning can help stakeholders address the multifaceted problem and adapt to changing conditions for long-term success [13].

The application of AI for food security involves a wide range of stakeholders and groups of people, such as farmers (e.g., commercial or smallholder farmers), agricultural researchers and scientists, food processing companies, food retailers and distributors, government agencies, NGOs, agriculture and food technology companies, and consumers [14]. Other stakeholders who also apply AI to enhance food security include investors and financial institutions, weather and climate agencies, supply chain and logistics companies, farm workers and labour forces, and food safety regulators, among other stakeholders [11]. The collaboration and coordination of these stakeholders are essential for addressing global food security challenges effectively [14,15].

In view of the stakeholders involved, in recent years, there has been a significant increase in investments by research agencies and governments worldwide in AI and its application in modelling food security issues [16]. Similarly, numerous research and policy organisations are actively developing models for effective policy making in the context of food security challenges [17]. Given the growing concerns regarding food (in)security, the scientific community recognises the crucial role of AI models in informing decision making. Despite the abundance of data and models available, there is often a failure in effectively translating these models into actionable policy [18–20]. A common characteristic of using AI in policy making is the interpretation of model outputs on a large scale [17,21,22]. While this approach is valuable, it is essential to integrate the local knowledge of stakeholders to ensure the robustness of model outcomes. The incorporation of stakeholders, their knowledge, and needs into models has been posited to result in better outcomes for stakeholders [23]. Involving stakeholders and incorporating their local knowledge in decision-making processes are necessary, as models alone can be ineffective tools [24,25]. Additionally, it is crucial to broaden the scope of model research to provide feedback to the communities under study [26]. Stakeholder participation requires collaboration with computer scientists and stakeholders [27], particularly the communities facing food insecurity. The approaches to stakeholder participation in AI modelling for food security vary [28].

Despite the diversity of participatory modelling methods to promote stakeholder involvement in modelling [29], particularly AI, the extent of stakeholder participation for food security purposes remains uncertain. Hence, there is little evidence that assesses stakeholder involvement in the application of AI models for food security. Also, limited knowledge exists on whether stakeholder involvement actually leads to a situation where AI modellers provide feedback to research communities. To this end, the main research questions that guide this study are as follows: What is the extent of stakeholder participation in AI modelling for food security? How does this engagement influence the feedback loop between AI modellers and local communities facing food insecurity?

As AI gains prominence in the food security sector, several studies have been conducted on s indicators of the technology. Similarly, studies have been conducted on food security and modelling (see, for instance, [16,18,21,30–34]). However, the existing studies consist of fragmented themes and methodologies in the agrifood sector, characterised by diverse objectives across different disciplines, with relatively few connections between AI and food security. Recognising the knowledge gap, this study aims to analyse the AI models used in the literature for food security research

This study contributes to the growing importance of AI in enhancing food security by emphasising significance of collaboration between computer scientists and stakeholders to incorporate local knowledge into AI models, making them more effective tools for decision making.

2. Literature Review and Conceptual Framing of the Research

This section defines the key concepts such as food security and AI modelling applied in this study.

- Defining food security

A sufficient global food production alone does not guarantee food security for the entire population [35]. Hence, nutrition security complements food security by considering individuals' ability to meet their nutritional needs through food intake [36]. Nutrition security is typically assessed at the individual level, taking into account factors such as gender, wealth, age, and other determinants that affect an individual's access to food within households [37]. Despite these differences, food and nutrition security indicators are commonly aggregated at local, regional, national, and global levels for policy-making purposes [38]. Therefore, in this paper, the term "food security" encompasses both food and nutrition security across scales.

Four indicators of food security—food accessibility, availability, affordability, and utilisation—are operationalised for analysis in this study [39,40]. Access refers to the amount of food that can be produced, purchased from the market, or obtained through other means [36,37]. The production of food is primarily connected to the food availability indicator of food security [41]. Affordability, the third dimension, pertains to the cost or price aspect of food, while utilisation refers to households' ability to process accessible food. This depends on their capacity to acquire sufficient fuel, water, and other resources specific to their contexts. Utilisation also relates to individuals' physiological ability to digest food [42].

Given the complexity of the challenges hindering the attainment of the indicators of food security, the sector requires innovative solutions to mitigate the trade-offs between environmental, economic, and social objectives while ensuring the short- and long-term accessibility, availability, affordability, and utilisation of food [43,44].

- The application of AI models in the context of food security

Following Soori et al. [11], AI models can be categorised as follows: (i) machine learning models; (ii) neural network and deep learning models; (iii) data mining, knowledge discovery, and advanced analytics models; (iv) rule-based models and decision-making models; (v) fuzzy logic-based approaches; (vi) knowledge representation, uncertainty reasoning, and expert system models; (vii) case-based reasoning models; (viii) text mining and natural language processing models; (ix) visual analytics, computer vision, and pattern recognition models; and (x) hybridisation, search, and optimisation techniques. Hence, the AI models considered in this study encompass machine learning and deep learning models [27,45,46], including approaches that might not be typically considered as conventional AI; however, they have integrated AI techniques or algorithms to some extent in the models. AI models span a range from the global scale (e.g., food trade equilibrium models) to the local scale (e.g., farm-level crop models, bioeconomic models, or agent-based approaches) [30].

The design or framework of AI models is typically top-down, neglecting the local setting, local knowledge, and the goals and needs of study communities. In such an instance, AI models utilise cadastral, biophysical, bioeconomic, or socioeconomic data or data integration, but they fail to incorporate the perspectives of the study communities. Critics argue that this approach results in detached outcomes that do not accurately reflect real-life situations and may not address actual food security issues. Müller et al. [17] pointed out that the exclusion of stakeholders and relevant concerns in these models reveals a gap that reflects social injustice.

Consequently, decisions often involve a trade-off between choosing the "right" model for the task and selecting the easiest model for researchers to use [3,47]. Therefore, modelling research is often driven by the capabilities of models rather than the requirements of stakeholders. Although some models explicitly aim to incorporate stakeholders' views, it remains challenging and unsatisfactory because predicting the future of food security under long-term global change scenarios is difficult. Additionally, modellers may encounter difficulties when combining different models due to the lack of empirical or experimental data for model parameterisation [48].

The complexity of global change and its interactions with the food system necessitate a multi-system and interdisciplinary perspective in AI modelling to address intricate food system issues. Consequently, an emerging approach, known as participatory modelling [49–51], seeks to integrate stakeholders' perspectives to bridge the existing gaps and overcome other challenges. More recently, analyses conducted at the global or regional level have made progress in finding solutions that better consider the local realities of individuals (e.g., [52,53]). Furthermore, recent advancements have witnessed collaborative efforts among modellers from diverse organisations, nations, and fields of expertise. This collective synergy aims to significantly strengthen worldwide food security [17].

3. Research Method

This study applied a literature review method [54]. The systematic review involved the identification, selection, and critical appraisal of relevant research, and an analysis of data from selected studies. To ensure a high level of quality reporting, this study adhered to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [55]. This framework encompasses a checklist and a flow diagram, both of which are crucial for transparent reporting (see File S1 in Supplementary Materials). Figure 1 illustrates the flow diagram, providing a visual representation of the steps undertaken and briefly discussed in the following sub-sections.

3.1. Literature Identification

In the quest to identify studies pertaining to AI's role in food security, the study opted to use the Google search engine due to its comprehensive coverage of disciplines and interdisciplinary journal articles. The search queries included combinations of terms such as "Agricultural subsidy policies" AND "Food security" AND "Artificial Intelligence", "Farming systems" AND "Food security" AND "Artificial Intelligence", "Landownership" AND "Food security" AND "Artificial Intelligence", and "Cropping systems" AND "Food security" AND "Artificial Intelligence". The authors deliberately sought articles that focused on the concepts of food security and AI models (see Supplementary Materials File S1). While this approach aligns with the research objectives, it is worth noting that other studies and concepts may exist. Consequently, this article should be considered a foundational step in the discourse on the application of AI models for food security, offering insights for future research and collaborative efforts. The search was not limited to specific journals or subsets of the literature. Given this study's emphasis on AI modelling in the context of food security, the authors conducted a broad search using terms such as "Food security", "Artificial Intelligence", "Machine learning", and "Modelling" during the abstract screening process, examining the title, abstract, and/or keywords of all articles in the database. This search was performed in December 2022 and yielded 1400 papers. To assess their relevance, the abstracts, introductions, and discussion sections, were thoroughly reviewed, resulting in the inclusion of 389 documents. Subsequently, 262 documents were selected due to removal of 127 duplicate documents.

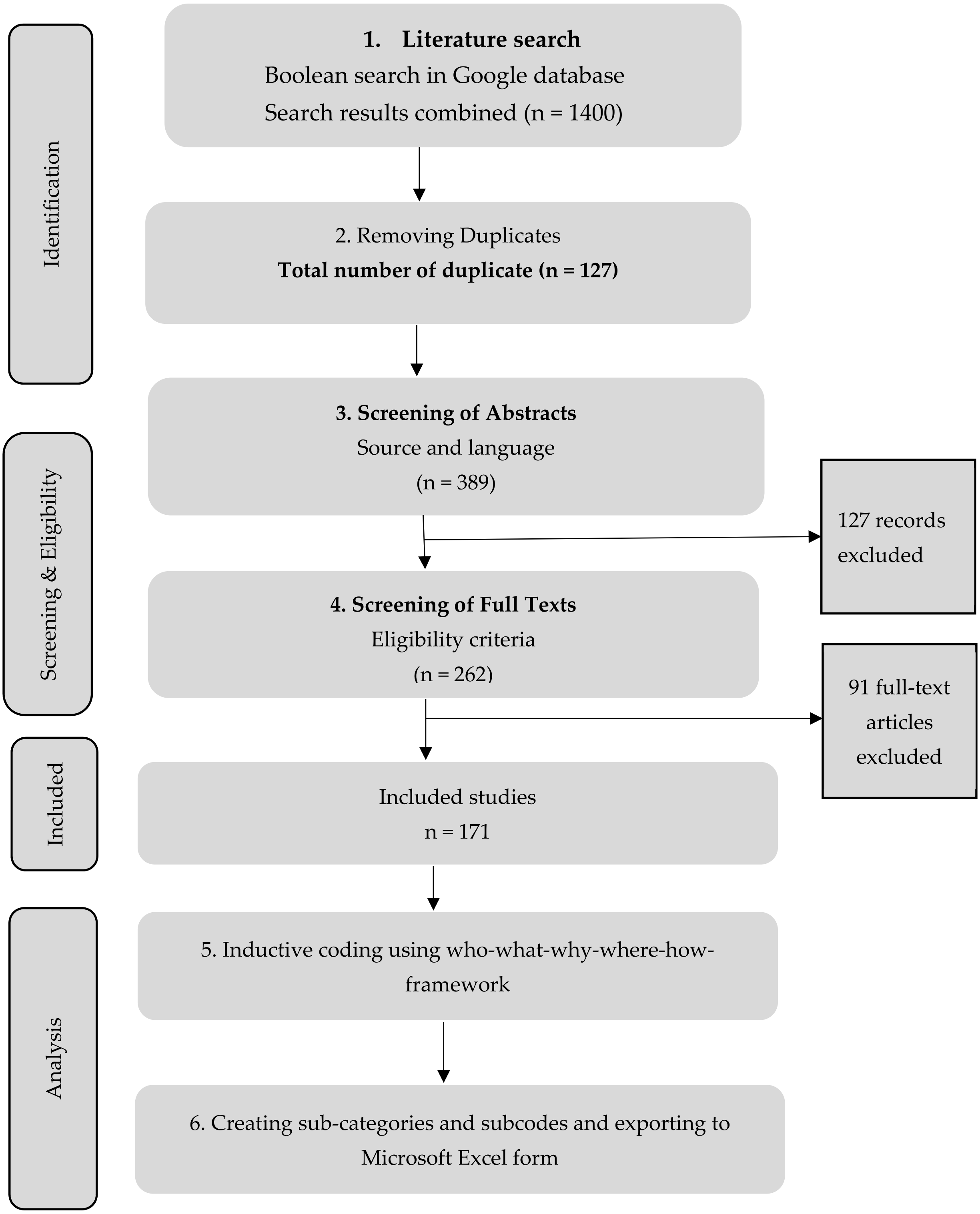

Figure 1. Schematic diagram of systematic review process.

3.2. Literature Screening and Eligibility

To assess the eligibility of the retrieved documents, this study established inclusion criteria. Studies failing to meet these criteria were excluded (n = 91). The selection criteria encompassed explicit references to methodologies for primary data collection and analyses concerning AI models or AI-related models, or indicators of food security. Another criterion focused on studies published in the English language from 2000 to 2022, as this period reflects the emergence of AI technologies and global food security discourses. Geographical coverage was also considered in our criteria. Ultimately, 171 articles met all inclusion criteria.

3.3. Analysis of Articles

The selected articles were imported into Atlas.ti software (version 22.1), where they were examined and categorised based on objectives, research methods, discussion, and conclusions. Atlas.ti's software capabilities facilitated the systematic organisation, coding, and analysis of qualitative data, such as text. It enabled annotation and data segmentation, the creation and application of hierarchical coding schemes, and the generation of reports and summaries. This software proved valuable for conducting in-depth content and thematic analyses of the selected documents. Each study underwent a thorough reading and coding process.

The method for analysing the selected documents primarily followed an inductive approach. In the initial phase, coding began with a list of codes for broad categories guided by the "who-what-where-why-how" concept. For example, under "where", coding initially encompassed geographical locations and subsequently generated sub-codes for specific regions (e.g., Asia, Africa, America, and Europe). For "why", coding examined the rationale, and open coding was employed to capture various aspects. Similarly, "how" aspect followed open coding, encompassing all relevant activities, including the models applied in each study. This approach allowed for the development of a comprehensive and detailed understanding of all the documents, linking broad themes and sub-codes together for the purpose of report writing. Coding encompassed the authors' institutions, funding organisations, study country/community, the model's end use, and food security indicators. Additionally, the theoretical underpinnings of the selected papers, focusing on the key concepts and constructs relevant to AI model research on food security (see Section 2), were coded.

Subsequently, codes for overarching themes (broad codes), such as geographical locations, indicators of food security, institutions conducting AI modelling research, and organisations funding AI models for food security research, were exported into Microsoft Office Excel 365 (Microsoft Corporation, Redmond, WA, USA). During this phase, more specific sub-codes were identified inductively. For instance, five sub-categories (i.e., development agencies, research institutions, state organisations, financial institutions, and others) were derived under the theme "organisations funding AI models for food security research". Subsequently, the data on categories and sub-categories in the extraction table were analysed for frequency of occurrence, leading to the creation of visual diagrams with Microsoft Office Excel. The results of the analyses are presented in the Findings Section. The analyses were not meant to generalise findings but rather identify pertinent research avenues for scholars to pursue context-specific investigations.

4. Findings

This section presents the findings categorised into sub-sections.

4.1. Overview of Geographical Locations of AI-Based Modelling Research on Food Security

The analysis of the selected documents showed the application of AI models for food security research in 68 countries across 6 continents. The distribution of the studies conducted in each continent is as follows: Africa (58 countries), Europe (17 countries), South America (16 countries), Asia (38 countries), North America (9 countries), and Australia

(4 countries). Additionally, some studies (30) had a global focus or focused on countries in different continents.

Among the 68 countries identified, approximately one-third of the studies were from the Global North [56–58], while two-thirds were from the Global South [24,59,60], with a particular emphasis on sub-Saharan African countries, like Ethiopia, Ghana, Malawi, Uganda, and Madagascar [61–67]. The European countries where research on AI and food security was conducted include Hungary, Spain, the UK, Italy, Poland, the Netherlands, Germany, and Greece [68–72]. Figure 2 highlights the geographical distribution of the identified countries and regions in the analysis.

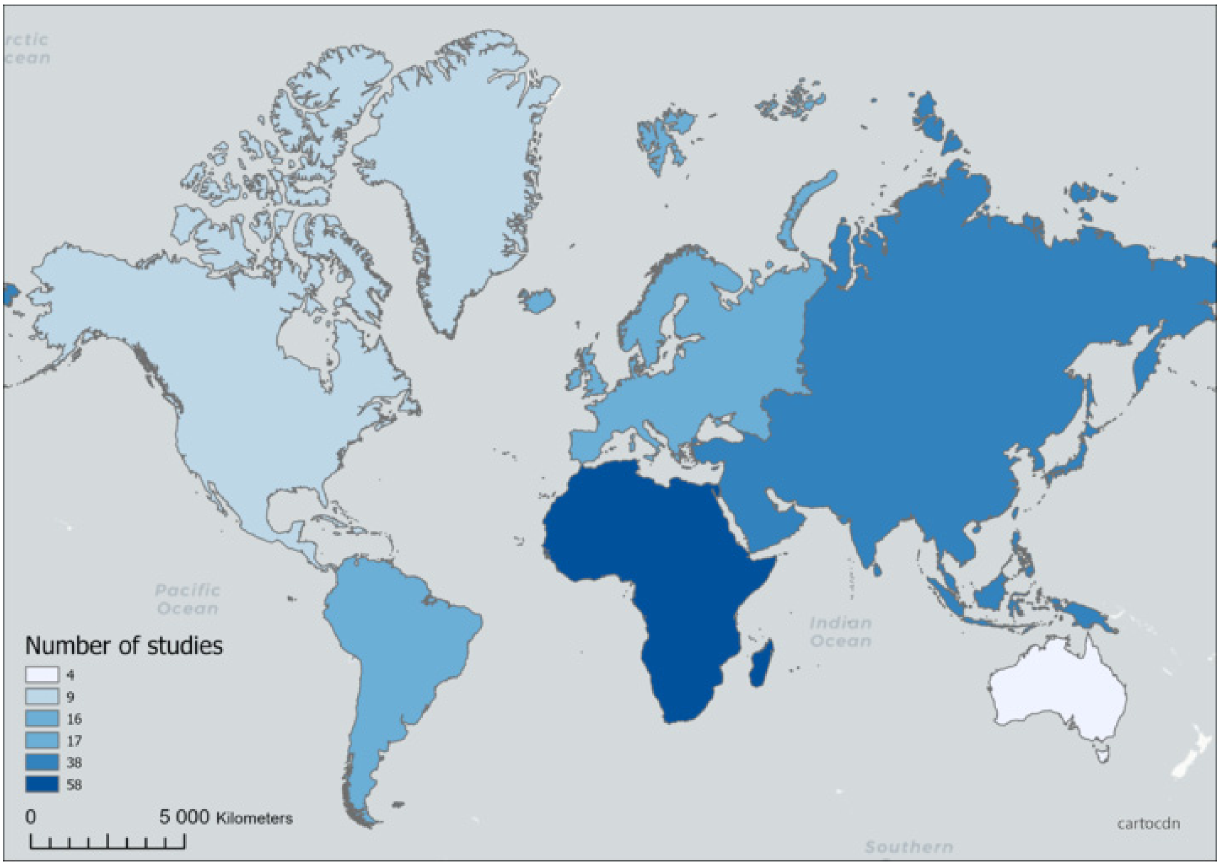

Figure 2. Geographical distribution of AI-based analytical research on food security. Source: authors' construct based on literature review, 2023.

4.1.1. Indicators of Food Security with the Application of AI Models

Research on AI and food security has analysed indicators, including accessibility, availability, affordability, and utilisation (Figure 3). However, most studies have primarily focused on the availability aspect of food security, often overlapping with other dimensions.

Regarding the accessibility indicator, 35 documents applied AI models to assess disparities in food distribution among households. These studies demonstrate how households rely on social safety programs or adopt coping strategies such as rural migration or the selling of livestock to improve their food security status [73–75].

Out of the 171 documents analysed, 105 documents mainly focused on food production, representing the availability indicator of food security [41]. The following themes provide an overview of the topics where AI has been applied to examine the availability indicator of food security:

- The impact of climate change on crop production, soil health, pest and disease patterns, and the vulnerability of crops [60,76,77].

- Predictions of changes in arable land cover, land use, and land use management under climate change [56,78–81].
- The effects of soil fertility decline, population growth, and poverty dynamics on food availability [59,82] and the application of climate or seasonal forecasts for food crop production [67].
- Agricultural productivity; crop yield predictions; risk; and the application of inputs, such as fertilisers, cropping patterns, sowing dates, crop variety selection, and cultural practices (like mulching and cropping patterns [43,65,79–87].
- Climate change and the contribution of livestock, aquaculture, and fisheries sectors to food availability [83,84].
- The potential of agricultural production systems, including smallholder farming systems, climate-smart agriculture, agroecology, agroforestry, industrial crops, organic farming, and the sustainable intensification of food crops [49,51,64,72,85–88].
- Farmers' behaviour, drivers, decision making regarding cropping patterns, input applications, and climate adaptation measures [89,90].
- Water availability, including groundwater and freshwater resources, irrigation dynamics, and management [25,91–94].

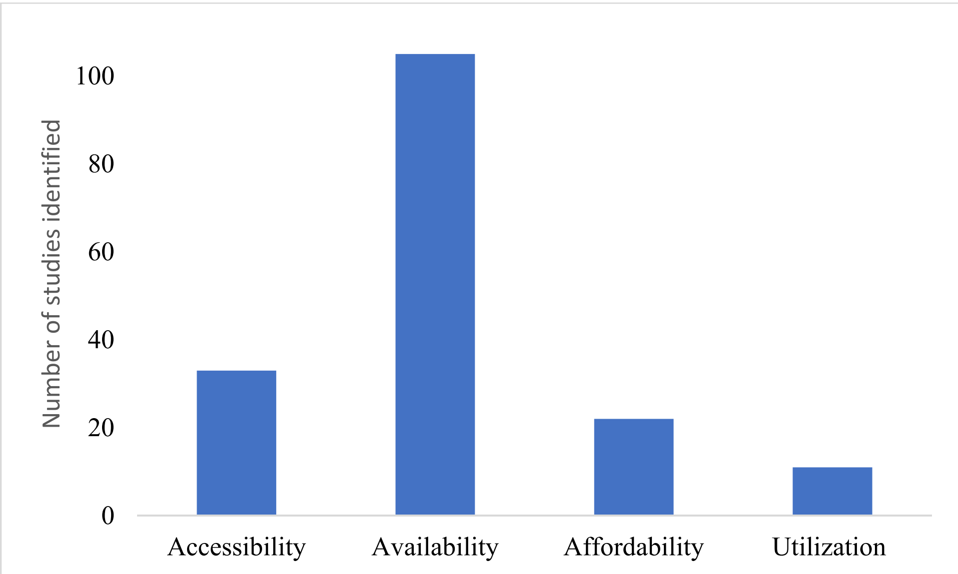

Figure 3. Indicators of food security analysed with AI-based model.

The crosscutting issues identified under the availability indicator of food security, with the application of AI models, include gender, labour issues, migratory household patterns [61,81,95–98], finance [99], cooperatives, local knowledge, infrastructure, supply/value chain [100–106], the energy–water–food nexus [107,108], and the application of digital technologies.

The affordability indicator of food security in AI model studies was limited to 22 documents, which explored the effect of subsidy policies on the food security of rural households [70,109]. These studies used models to create scenarios, examining conditions such as the taxation of groundwater extraction, increased water costs, reductions in agricultural subsidies, and cash transfer programs and the effects on rural livelihoods and food security [110]. Additionally, two document nvestigated the impact of food prices on food security and household income [62,111], particularly in sub-Saharan Africa. An AI model based on machine learning algorithms was also employed to estimate the role of scarcity, prices, food riots, and politically unstable regions [112].

AI models were also applied to assess the utilisation of food. The analysis also showed 11 documents focusing on social influence and the consumption patterns of specific food products, such as dairy [58,113,114] and plant-based meat alternatives. With this category, models were also used to explore the food utilisation of different farming styles and their impact on hunger and rural health [115]. Other identified themes included social capital and the nutritional status of various groups, mainly rural farm households [116–118].

In this study, food security indicators were assessed at multiple levels, ranging from local to global (see Table 1).

Table 1. The application of AI models for food security indicators at various levels.

Indicators	Levels of Application of AI Models for Food Security Research				
	Local	**Sub-Regional**	**National**	**Regional**	**Global**
Accessibility	n = 23	n = 1	n = 8		n = 3
Availability	n = 47	n = 17	n = 11	n = 5	n = 23
Affordability	n = 19		n = 2		n = 1
Utilisation	n = 6		n = 1	n = 1	n = 3

Availability was the most frequently measured food security indicator across all levels, with data available at the local, sub-regional, national, regional, and global levels. This suggests a strong focus on assessing the quantity and availability of food. Accessibility indicators were examined at the local level (e.g., communities, villages, household, farm levels, and suburbs), in 23 documents. This assessment focused on whether households within these specific localities have sufficient access to food. The sub-regional level (e.g., watersheds, river basins, sub-regions, and provinces) was also considered in this study, with data collected from 1 document. This study extended its analysis on the accessibility indicator to the national level, involving data from 8 documents. The regional level (e.g., the European Union) analysis involved 3 documents, and, at the global level, this study examined food security indicators from a broader perspective. It included data from 23 documents.

Accessibility was also researched at various levels, including local, national, and regional levels, indicating an interest in understanding whether people have physical and economic access to food. Affordability was identified at the local and national levels, focusing on whether individuals and households can afford to purchase food. However, it was not assessed at the sub-regional, regional, or global levels. Utilisation was the least measured indicator, with data primarily available at the local and regional levels. Utilisation assesses how well individuals within a household utilise the available food, including nutritional aspects. It was not assessed at the sub-regional, national, or global levels. There was limited data at the sub-regional, regional, and global levels for most indicators, showing that food security assessment is often conducted at the local or national levels. The distribution of data across these indicators and levels suggests that food security assessments may vary in scope and depth, with a stronger emphasis on assessing the availability and, to a lesser extent, the accessibility and affordability of food. The absence of data at the global level for some indicators may be due to the challenges of collecting consistent with specific indicators of food security.

4.1.2. Model Types

This study identified various types of models; however, there were differences in their applications. Some studies applied a combination of models, including systemic and dynamic modelling. For instance, the ALUAM-AB model, an economic land use model based on Linear Programming Language (LPL) and a CPLEX solver, was applied to assess land use changes and their corresponding effects on food production and farming decision making. The models mentioned in the reviewed documents analysed human factors (such as the adoption of technologies, labour availability, and migration patterns), natural systems (weather, soil, water, etc.), or a combination of both. Machine learning algorithms, such as Boosted Regression Trees (BRT), Random Forest (RF), and Maximum Entropy (MAXENT) algorithms, were identified, mainly focused on analysing natural systems. Additionally, agent-based modelling approaches, like the Common Resources Management Agent-Based System (CORMAS), Companion Modelling (ComMod), and RaMDry, were applied. As mentioned in Section 2, the identified models in Table 2 also include techniques that used AI algorithms at some stages.

Table 2. List of models applied in research on indicators of food security.

Models Applied in Food Security Research	Application in the Reviewed Documents	Type of Approach Adopted
Farm management model FARMACTOR and crop growth model system EXPERT-N	Crop management and decision making regarding planting and harvesting [69]	Natural systems
GIAM.GTEM [119]; Global and Local Learning Model, GALLM) (Hayward and Graham, 2013) [120]	Explored the response of land use and agricultural production to changes in productivity rates, resource scarcity and degradation, greenhouse gas abatement policy, climate change, and global demand [78]	Natural systems
Statistical Analogue Resampling (STAR) scheme, Weather and Research Forecasting (WRF) model, and Model for Nitrogen and Carbon in Agroecosystems (MONICA)	Evaluated the impact of two climate change scenarios on the profitability of double-cropping systems [60]	Natural and human systems
GIS modelling, Analytic Hierarchy Process (AHP), and an optimisation functionality	Assessed the "Energy-Water-Food nexus node" to support decision making for sustainable and resilient food security [108]	Natural systems
Markovian cellular automata and an agent-based approach	Investigated the future land use trajectories of a semi-arid Mediterranean agroecosystem [121]	Natural and human systems
Computable General Equilibrium (CGE) model	Seasonal rural labour markets and their relevance to policy analyses [81]	Natural and human systems
Discrete Event Simulation	Simulated potential growth strategies and observe the impact concerning existing farm processes [122]	Natural and human systems
Change detection methods and agent-based modelling	Examined of historical and future land use changes [118]	Natural and human systems
ADOPT (combines socio-hydrological and agent-based modelling approaches by coupling the FAO crop model AquacropOS with a behavioural model capable of simulating different adaptive behavioural theories)	Evaluated the factors that influence adaptation decisions and the subsequent adoption of measures and how this affects drought risk for agricultural production [90] Farmers facing droughts: capturing adaptation dynamics [25] Education, financial aid, and awareness can reduce smallholder farmers' vulnerability to drought [99]	Natural and human systems
The ID3 rule induction/machine learning algorithm	Assessed farmers' adaptation to changes in environmental and economic contexts [68]	Natural and human systems
MOSAICA	Assessed the upscale of CSA [51]	Human systems
Machine learning algorithms, including Boosted Regression Trees (BRT), Random Forest (RF), and Maximum Entropy (MAXENT) algorithms	Mapped the suitability for small-scale, informal irrigation [94]	Natural systems
GIS and agent-based modelling	The interlinkage and interaction of resource–food–bioenergy systems and optimise supply chains considering poly-centric decision spaces [123]	Natural systems
Remote sensing and Artificial Intelligence techniques (neural network algorithms)	Identified of food insecure zones [95]	Natural systems

Table 2. *Cont.*

Models Applied in Food Security Research	Application in the Reviewed Documents	Type of Approach Adopted
CLASSES (bioeconomic system dynamics model) and Mexico Sheep Sector Model (MSSM)	Illustrated how three indicators of access (food consumption expenditures, a food insecurity scale, and dietary diversity) and their stability can be incorporated into a dynamic household-level model of a maize-based production system and a dynamic regional model of sheep production and marketing [98]	Natural and human systems
Artificial Intelligence and deep learning approaches	Agricultural productivity and crop yield predictions and risk [124–130]	Natural systems
Model for Nitrogen and Carbon Dynamics in Agroecosystems (MONICA) and Mathematical-Programming-based Multi-Agent Systems (MPMASs)	Identified biophysical and socioeconomic dimensions of yield gaps [59]	Natural and human system
MPMASs with the crop growth model Model for Nitrogen and Carbon in Agroecosystems)	Examined farmers' decision making and agricultural land use to account for the interplay between the environment and human decision making [89]	Natural and human system
Common Resources Management Agent-Based System (CORMAS) and SimSahel model	Tested the impact of social forces on the evolution of Sahelian farming systems [85]	Natural and human systems
Asia-Pacific Integrated Model (AIM) using Computable General Equilibrium	Inclusive climate change mitigation and food security policy [96,97]	Natural and human systems
Agent-based model	The potential effects of a subsidised policy on households to rent out land use rights for long terms under formal contracts and impacts on food security [109]	Natural and human systems
	Examined impacts of climate and price variability on household income and food security [62]	Natural and human systems
	Assessed of household-level and community-wide resilience to climate shocks in a smallholder mixed crop–livestock farming setting [84]	Natural and human systems
	Assess future patterns of arable land use under four localised, stakeholder-driven scenarios of plausible future socioeconomic and climate change [80]	Human systems
	Integrated of seasonal precipitation forecast information into local-level agricultural decision making [67]	Natural and human systems
	Milk consumption and scenarios of dairy reduction and adoption of plant-based milk (PBM) [58]	Natural and human systems
	Simulated the impacts of climate variability and change on crop varietal diversity [131]	Human systems
	Irrigation agriculture dynamics [91,93]	Natural and human systems
	Explored how interactions between households and the environment lead to the emergence of community food availability, access, utilisation, and stability over time [61]	Natural and human systems
	The impacts of cash transfer programs on rural livelihoods [110]	Natural and human systems
	Transition from conventional to organic farming [91]	Natural and human systems

Table 2. *Cont.*

Models Applied in Food Security Research	Application in the Reviewed Documents	Type of Approach Adopted
Agent-based model	Assessment of agricultural vulnerability of sugarcane facing climatic change [77]	Natural and human systems
	Characterising farm types and evolvement in smallholder dairy systems [113]	Natural and human systems
	Assessed the impacts of the changes in farming systems on food security and environmental sustainability of a rural region [76]	Natural and human systems
	The management of aquaculture production [83]	Natural and human systems
	Vulnerable households using migration to manage the risk of rainfall variability and food insecurity [74]	Natural and human systems
	Market of potato (Solanum tuberosum) producers [100]	Human systems
	The impact that water canals and electric grid development have on the Water–Energy–Food (WEF) nexus in a rural area [107]	Human systems
	Analysed the impact of climate-smart agriculture on food security using an agent-based analysis [88]	Human systems
	Simulate strategies of the perishable food market under different circumstances [104]	Human systems
	Reduced meat consumption [114]; social influence on meat-eating behaviour [132]	Human systems
	Examined the supply chain of organic fertiliser [102]	Human systems
	Evaluated food supply chain resilience: potato supply chain [105]; contract farming in rice supply chain [103,106]	Human systems
	Examined the uptake of new farming practices, for example, organic waste application [87]	Human systems
	Examined household food security, climate outlook, and agricultural productivity [133–137]	Natural and Human systems
	Examined climate change, hunger, and rural health through the lens of farming styles [115]	Natural and human systems
	Simulated small-scale farmers' agroforestry adoption decisions to investigate the consequences for livelihoods and the environment over time [138]	Natural and human systems
	Projected the effect of crop yield increases, dietary change, and different price scenarios on land use under two different state security regimes [111]	Natural and human systems
	Examined Food security and global trade [101]	Human systems
	Asses the potential of land use change for mitigation of food deserts [56]	Natural and human systems
	Analysed the diffusion of added-value markets among Dutch farmers [139]	Natural and human systems
	Examined disparities in food accessibility among households [117]	Natural and human systems
	Farmers' adaptation to agricultural risks [140]; adaptive management in crop pest control in the face of climate variability [141] postharvest loss of food grains [142]	Natural and human systems

Table 2. *Cont.*

Models Applied in Food Security Research	Application in the Reviewed Documents	Type of Approach Adopted
Dimensions of Agent-Based Modelling Approaches		
Common Resources Management Agent-Based System (CORMAS) [143,144]	Assessed development intervention on the provision of fertiliser and credit to farmers [73]	Natural and human systems
TERROIR (TERRoir level Organic matter Interactions and Recycling model)	Analysed nutrient cycles at three levels of organisation: plot, household, and landscape [145]	Natural and human systems
AMBAWA model	Assessed the impacts of the practice of crop residue mulching on crop productivity [64]	Natural and human systems
Spatially explicit empirical agent-based model (SEALM)	Examined possible future trends of farmers' crop management and the effects of these trends on the environment, household economy, food self-sufficiency, and household coping strategies for food insecurity [65]	Natural and human systems
Companion Modelling (ComMod)	Assessed the synergies and trade-offs between REDD+ and climate-smart agriculture [49] Groundwater irrigation management with local farmers [92]	Natural and human systems
ALUAM-AB (an economic land use model based on Linear Programming Language (LPL) and a CPLEX solver)	Assessed the interaction effects of these agricultural policies while accounting for climate change impacts in the analysis [70]	Natural and human systems
Integrated assessment modelling (IAM) using coupled component modelling (CCM) approach to derive an agent-based model associated with a soil model and multi-scale spatial model, resulting in the Model for West-Africa Agroecosystem Integrated Assessment (MOWASIA)	Assessed the environmental and economic performances of semi-continuous and continuous farming systems [146]	Natural and human systems
Agent-based rangeland model RaMDry	Assessed the vulnerability of rangelands and livestock production systems as a result of the effects of ongoing changes in precipitation and its variation, as well as its temporal distribution [75]	Natural systems
Multi-agent systems (MAS)	Simulated soil fertility and poverty dynamics [147] Simulation of the sustainability of farming systems [148]	Natural and human systems
Mathematical Programming-based Multi-Agent Systems (MPMASs)	Analysed how adaptation affects the distribution of household food security and poverty under the current climate and price variability [82] Analysed of the biophysical and socioeconomic factors that influence the livelihood strategies of traditional Andean farmers and study how these systems are being affected by climate change [149] Climate variability, social capital, and food security [143] Examined watershed-level irrigation management [150]	Human systems
The OMOLAND-CA (OMOLAND Climate Change Adaptation) model	The socio-cognitive behaviour of rural households towards climate change and resource flows prompt agents to diversify their production strategy under different climatic conditions [116]	Models natural and human systems

Table 2. *Cont.*

Models Applied in Food Security Research	Application in the Reviewed Documents	Type of Approach Adopted
The farm management model (FarmActor)	Examined how climatic changes drive farmers' adaptation of their land use decisions [151].	Models natural and human systems
Common Resources Management Agent-Based System (CORMAS)	Analysed the impact of development interventions on the rural population [85]	Models natural and human systems
Flows in Agro-Food Networks (FAN)	Simulated contrasting scenarios of material flows locally in a small farming region [152]	Models natural and human systems
The Dawe Global Security Model	Simulated the global food market, food riot, and the political fragility of countries [112]	Human systems

4.2. Institutions Conducting AI-Based Modelling Research for Food Security

This study identified three categories of institutions that engaged in AI modelling research for food security. These categories are as follows:

1. Local organisations based in countries where the research was conducted, predominantly comprising universities or research institutions [70,76,78,108,122,131,153].
2. Collaboration was observed between local and foreign research institutions [59,60,80,81,113,121,154].
3. Foreign organisations, including universities and international research organisations, solely focused on AI research related to food security [24,49,62,65,66,73,84,109].

According to Figure 4, AI modelling research on food security was primarily led by foreign organisations. These collaborations involved universities and research institutions from the Global North, while the actual study communities were based in the Global South. The local organisations engaged in AI modelling research for food security in home-based countries were predominantly from developed countries [69,70,78]. However, there were exceptions, as local organisations carried out research in countries such as Qatar, Iran, China, South Africa, and Saudi Arabia [70,92,104,108,155].

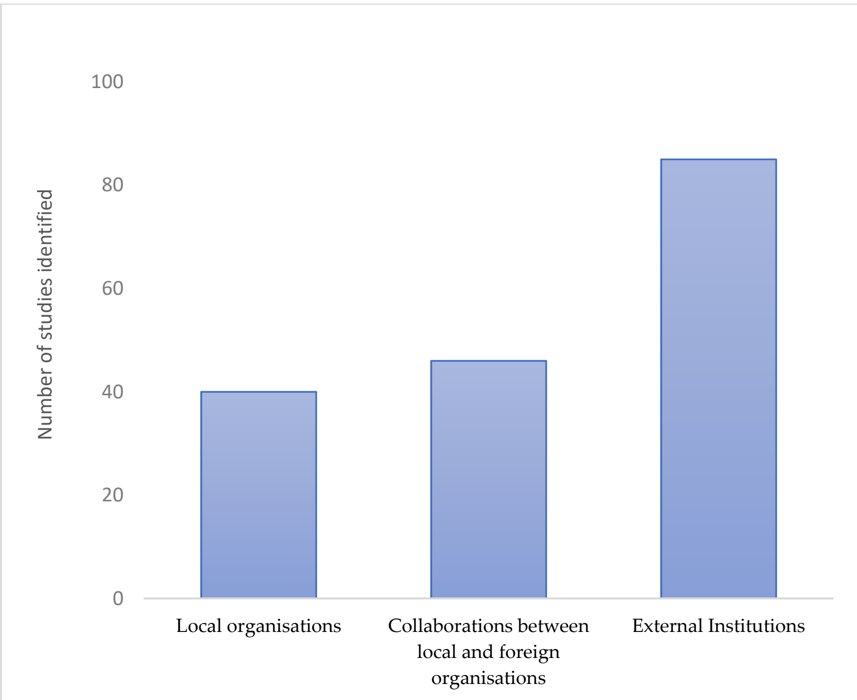

Figure 4. Origin of Institutions conducting AI-based modelling research on food security. Source: authors' construct based on literature review, 2023.

4.3. Categories of Organisations Funding AI Modelling Research on Food Security

This study identified three categories of funding for AI modelling research on food security as follows:

i. Foreign funding: AI modelling research on food security was funded by development agencies, research institutions, state organisations, financial institutions, and other forums (e.g., foundations or platforms) [24,31,49,59,64–66,84].
ii. Collaborative funding: Funding between local universities, research institutions, and foreign partners [89,155].
iii. Local funding: Home-based institutions (e.g., local universities and research institutes) received funds from governments through research councils [58,69,70,72,78,108,113].

Figure 5 illustrates findings on the three modes of funding for AI modelling research for food security. However, collaborative funding (i.e., the contribution of funds between a home-based institution and external partners) was less than sole foreign funding. In some instances, home-based institutions provided support to research in kind. Of the 171 papers reviewed, 36 funding sources could not be identified, as the documents did not mention any funding organisations.

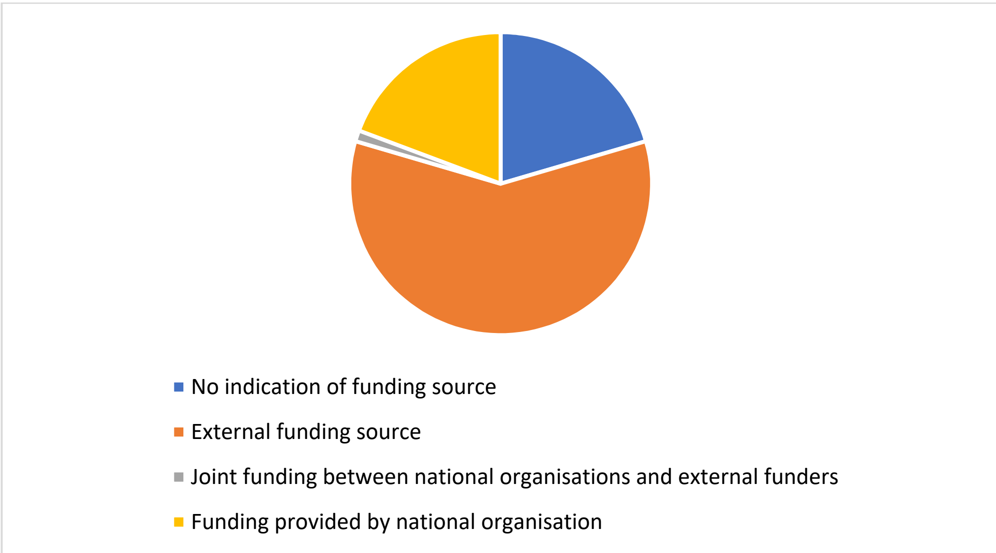

Figure 5. Sources of funding for AI-based modelling research on food security. Source: authors' construct based on literature review, 2023.

External funding for AI modelling research for food security was provided by development agencies, research institutions, state organisations, financial institutions, and others (refer to Figure 5). For example, funding for AI modelling research on food security was received through initiatives such as the CGIAR Program on Water & Food; "Meeting Urban Food Needs", a project by the Food and Agriculture Organization of the United Nations; the Global Hunger and Food Security Initiative of the United States Agency for International Development (USAID); and the West African Science Service Center on Climate Change and Adapted Land Use (WASCAL), among other initiatives (see Supplementary Materials File S2). Figure 6 illustrates the distribution of external funding sources for AI modelling research on food security. The analysis showed 103 reviewed documents that mentioned external funding. However, the analyses showed 150 organisations because some documents stated more than one external funding organisation.

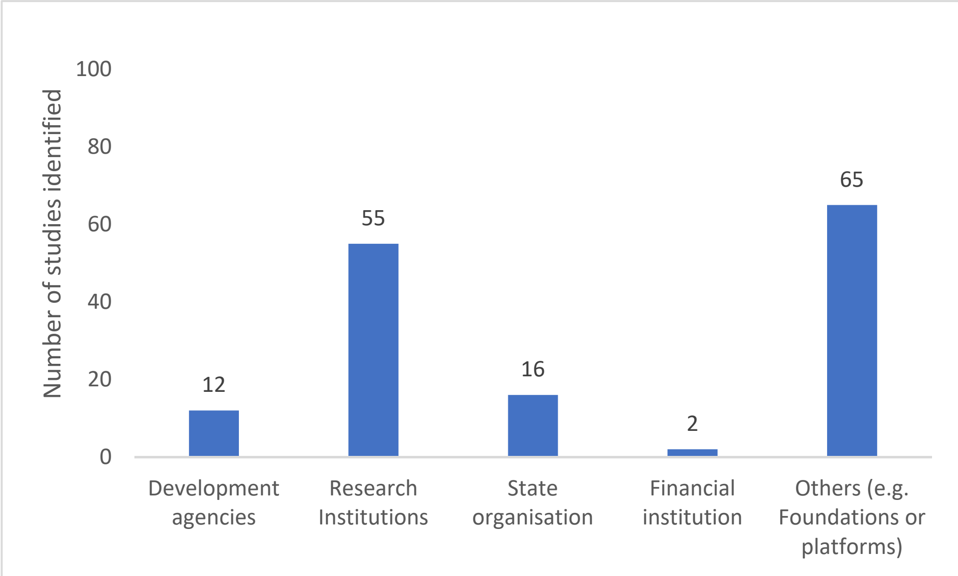

Figure 6. Sources of external funding for AI-based model research. Source: authors' construct based on literature review, 2023.

External funding for AI modelling research on food security has primarily focused on countries in the Global South, particularly Africa. These countries include Niger, Senegal, Ethiopia, Burkina Faso, Tanzania, Madagascar, Ghana, Uganda, Malawi, Kenya, Cameroon, and South Africa [61–67]. A similar funding pattern was observed in the Asian region, specifically in Laos, Vietnam, Bhutan, Thailand, Indonesia, India, Sri Lanka, the Philippines, Bangladesh, and Nepal [49,81,109,149]. In South America, the countries identified included Paraguay, Brazil, Colombia, Peru, Mexico, Chile, Guadeloupe, Uruguay, Ecuador, and Guatemala [24,59,60,91,100,149,156].

In the Global North, government and national/local organisations provided funding for AI modelling research on food security in countries such as Germany, Switzerland, the UK, Norway, Australia, the USA, Canada, the Netherlands, France, and Belgium [68–72]. In the Mediterranean and Arab (MENA) region, countries like Qatar, Iran, and Saudi Arabia have foundations or government-sponsored initiatives for AI modelling research on food security [108,155]. While most modelling studies on food security in the Global South were externally funded, there were a few exceptions where some local institutions also financed research activities on food security [76,136,157].

4.4. Approaches Used in AI Models for Food Security Research

This section analyses three main approaches commonly adopted in AI model research on food security. These approaches are as follows:

4.4.1. The Application of Only Artificial Intelligence Models for Food Security Situations

The first approach identified in the studies (87 documents) used various types of data without involving stakeholders. The data sources included biophysical data (such as crop data, weather/climate data, and soil characteristics data), bioeconomic data (including historical agricultural production data), and cadastral data (such as satellite images, geospatial information, and land use and landcover maps). In some studies, different datasets were integrated into models to investigate specific aspects of food security.

The recommendations and conclusions reflected on the model building process and the potential of AI to conduct specific analyses, frameworks, and methodologies. Ultimately, they offered insights into the possibilities and limitations of the models, such as the unavailability of data for model development, evaluation, and application. Furthermore, the studies drew conclusions on the future operationalisation of the model for food security and proposed avenues for future research, including the incorporation of parameters, variables, socioeconomic and environmental factors into the models. However, a few studies recommended involving stakeholders when applying the model outputs in real-life situations.

4.4.2. Involving Stakeholders in Artificial Intelligence Model Research for Food Security

The second approach identified in the reviewed literature (81 documents) involved integrating AI models, biophysical data, and primary data derived from stakeholders. Data utilised for this approach encompassed preliminary data gathered through various methods, including participatory research, surveys/questionnaires (using the Likert scale, open-ended formats, and close-ended formats), focus group discussions, interviews, Bayesian network analysis, workshops, role-playing games, community meetings, observations, and ethnographic approaches (refer to see Supplementary Materials File S3 for more details). In certain studies, mixed methods were employed to harness the benefits of integrating real-life data with models. Some studies utilized a research methodology involving field investigations, local experts' discussions, and interdisciplinary modelling. Some studies developed parameters and scenarios with stakeholders. Stakeholders also supported the modelling process, for example, participating in the validation and simulation stages. Additionally, studies identified in this category also applied secondary data in the form of a literature review, consisting of peer-reviewed literature, project reviews, and government documents outlining government directives, as well as food security strategies and planning. The secondary data sources (e.g., census data) were applied in some studies to construct scenarios for the models.

With this approach, models also applied well-known concepts from sociology, science communication, and economics to study indicators of food security. Although the studies reviewed under this category included stakeholders' perspectives, their main focus was building a modelling framework to explore the extent of food security indicators. The discussions of findings, recommendations, and conclusions proposed how policy and research results could enhance productivity and food security. Most studies analyzed the effectiveness of the methodology applied and recommended the use of mixed method approach and using an interactive and interdisciplinary approach to understand food security situations. Some studies in this category also recommended cross-validation and suggested pathways for future research, such as incorporating a larger sample size, developing the concept of value co-creation, and assessing the feasibility of different paths in practice.

4.4.3. Stakeholder Involvement in AI Modelling for Food Security through an Iterative Process

There was a limited application (3 documents) of this approach where stakeholders were involved in AI modelling for food security through an iterative process. Findings on this approach indicate the utilization of biophysical and real-life data, as described in Section 4.4.2. However, researchers shared their findings (feedback) with study communities and assisted in implementing the results. The modelling process involved workshops, conceptualization, scenario building, implementation, validation, and experimentation. Various methodologies combined tools and interpretations of remote sensing data in computer modelling (ComMod and multi-agent model). Stakeholder engagements involved conventional on-farm research, role plays, on-farm surveys, innovation platforms, farmer field schools, and experiments. The studies that applied these approaches reflected on the "best practice" of involving stakeholders, and it provided entry points to engage stakeholders, integrated knowledge from diverse sources and identified methodological choices that could be replicated. They also mentioned capacity-building initiatives, as well as monitoring and evaluation as means of critical reflections and learning on the successes and failures. Studies identified for the analysis under this category communicated or provided feedback to research communities. Conclusions also demonstrated that local stakeholders' involvement enhanced the design of local interventions, tailoring them to fit the specific context.

5. Discussion

In this section, the key themes that emerged from the research findings are discussed.

This review conducted on the use of AI models for food security purposes revealed few studies that have demonstrated how feedback is incorporated into policy or even implemented the outcomes with stakeholders. The approach to go beyond AI modelling and stakeholder consultation was observed in three studies in the analysis that employed participatory modelling, involving stakeholders' knowledge to develop formalised and shared representations of reality. These studies used models as boundary objects to facilitate two-way learning and collective reasoning about food security challenges iteratively. The limited provision of feedback and implementation of outcomes in study communities, as identified in several studies, may be attributed to the current organisation of research, where there is more focus on model outputs for publications to fulfil aspects of funding indicators. Moreover, the limited timeframe of consortiums can result in a lack of continuity in applying research outcomes in communities. The funding issues and the organisations responsible for implementing AI modelling research may also influence the selection of research designs, including the provision of feedback and the implementation of findings.

This study also found that the sources of funding for AI modelling research on food security were predominantly external to study communities. Most of the reviewed studies indicated that researchers initiated the research process rather than the local population. This finding has implications for the implementation of AI models for food security to address local needs. Hence, it highlights the need for local stakeholders to take the lead in setting the research agenda, rather than relying solely on researchers and funding agencies. The findings also emphasises the importance of promoting the use of AI technologies for demand-driven innovation and scaling approaches.

The findings on the themes of food security, for example, climate-smart agricultural practices, agroecology, climate information services for agriculture, and sustainable agricultural practices, among other related themes, align with the current agenda set by international donor agencies and organisations for global food security and food systems. According to Verburg et al. [19], most research grants for modelling in the crop and agricultural sector, for instance, are driven by specific issues, with model development and implementation often serving as secondary objectives. This study also calls for the international community to critically review the approach to funding research, especially for AI modelling research on food security, as it has shed light on the missing link between researchers and stakeholders, especially local communities.

Also, studies did not adequately address or even document how they dealt with issues regarding inclusiveness and the equitable and fair representation of stakeholders and vulnerable groups in the selection of stakeholders. In addition, the documents analysed lacked explicit statements justifying the selection criteria of stakeholders. The documents reviewed also did not illustrate how they created separate interaction spaces for different groups of stakeholders. Additionally, the studies did not consider selection criteria for participating stakeholders, including researchers. The consideration of AI researchers in the food security sector as stakeholders in the research can strengthen the research framework and outcome for practical implementation.

The findings in Section 4.4.2 show that some studies used already established interaction spaces from previous or ongoing projects, such as innovation platforms and farmer field schools. These spaces incorporated stakeholders who were already actively involved in knowledge production, sharing, and use. Examples of such stakeholders include opinion leaders, extension agents with good relationships with farmers, experts recognised by their peers, and individuals with extensive networks. However, only a few studies explicitly stated how they applied interactive principles, such as involving stakeholders throughout the process, creating opportunities for mutual learning, and monitoring and assessing mutual learning (as mentioned in Section 4.4.3).

While many models fall short in addressing inclusivity and fairness when dealing with food security challenges, establishing some points of departure can help provide context and relevance to modelling approaches. One such point is determining whether AI modelling approaches can solve all food security challenges. Answering this question requires selecting approaches that promote inclusivity and accurately reflect people's realities. However, considering the wide range of realities and priorities, achieving this goal may prove challenging, particularly for local communities. Moreover, modellers often tend to adhere to their conventional approaches and define realities based on their own preferences.

In the documents reviewed, especially those that involved stakeholders, there was an observed discrepancy where the studies tried to encompass broad perspectives while simultaneously addressing contextual issues. In this instance, there are risks associated with applying AI models to study food security on a global scale. However, there is also recognition regarding the issue of scale and the trade-offs associated with it, as it can influence the extent to which AI modelling research can facilitate social justice and equity in addressing real-life food security challenges. Consequently, these intriguing dilemmas prompt the need to consider how we can navigate the issue of scale in models.

In some studies, the primary goals of the models were focused on model building and framework development, rather than employing the models to solve specific food security challenges. Also, the development of models has been characterised by gradual, often ad hoc improvements and extensions, with different groups incorporating "new" modules that have already been implemented elsewhere [17]. Consequently, there has been an increase in the number of models, but insufficient attention has been given to other crucial processes related to food security, such as addressing perennial challenges, and bridging the gap between simulated and actual on-farm yields [19]. Here, this study proposes that, instead of viewing models as black boxes, they should be seen as internally logical tools that can lead to specific outcomes on food security challenges, thereby persuading stakeholders to adopt appropriate actions.

Contributions of This Study to Policy and the Scientific Community

One key contribution of this study is the identification of different categories of institutions involved in AI modelling research on food security. This study highlights the dominance of foreign organisations, mainly from the Global North, in spearheading AI modelling research on food security, despite the research communities being based in the Global South. This information is vital for policymakers and researchers to ensure inclusivity and equity in AI modelling research on food security, promoting a balance between local and foreign involvement. Another contribution of this study is the comprehensive overview of the organisations funding AI modelling research on food security. This article identifies three modes of funding for AI models, including foreign funding, collaborative funding, and local funding. Additionally, it presents a detailed analysis of external funding sources for AI modelling research on food security, with a focus on countries in the Global South, North, and MENA regions. By providing this information, this article offers valuable insights into the global funding landscape for AI modelling research on food security, which can inform future research and policy decisions in this field.

This study also identified three approaches: one focusing on biophysical and bioeconomic data and the other focusing on integrating local knowledge and experiences through stakeholder involvement. This study emphasises the importance of stakeholder participation in developing policy instruments to improve food security, such as subsidies, infrastructure deployment, economic and market incentives, and extension and advisory systems. Additionally, it discusses the limited involvement of stakeholders throughout the research process, including the provision of feedback and implementation of research outcomes, providing insights into the potential benefits of increased stakeholder engagement, such as promoting participatory monitoring and evaluation and tailoring interventions to fit the local context.

The findings of the study have implications for policymakers, researchers, and practitioners working towards achieving food security and promoting sustainable development. Overall, this study contributes to the growing body of knowledge on the application of AI in addressing global challenges like food insecurity.

6. Conclusions

In conclusion, the analysis of geographical locations, indicators of food security, model types, institutions involved, and funding sources in AI modelling research on food security has revealed both the global scope and the intricate web of stakeholders engaged in addressing this critical issue. However, the multifaceted problems surrounding food security persist, demanding continued attention and innovative approaches for involving stakeholders. One of the key takeaways from this review research is the significant emphasis placed on the availability indicator of food security through AI modelling, with research predominantly concentrated in sub-Saharan Africa. While this focus is crucial, it is important to recognise that the affordability and utilisation aspects of food security also warrant closer examination, as they are interconnected with the broader food security landscape. Moreover, the integration of stakeholders, local knowledge, and community participation in AI modelling research on food security has demonstrated its potential for generating meaningful insights and real-life interventions. This approach can lead to a shift in community perceptions, promote trust, and empower marginalised groups to participate in decision-making processes. As we navigate the complexities of ensuring food security in a changing world, it is evident that collaborative efforts between researchers, stakeholders, and local communities are essential. Only by engaging in iterative processes that bridge the gap between theory and practice can we hope to address the multifaceted challenges of food security effectively. Through such inclusive approaches, we can drive meaningful change, enhance food security, and ultimately contribute to a more sustainable and equitable future.

Based on the findings of this study, this study proposes the following recommendations to enhance research on the application of AI and food security.

There is a need to build trust between researchers and study communities to maintain long-term collaborations. This can be achieved through informal, shared experiences that build social capital among researchers, stakeholders, and communities facing food security. Trust can be built when AI modellers (research groups) acknowledge, examine, and appreciate differences in the study community's traditions and experiences and select methodological approaches that foster engagement. It is essential for researchers to fully understand the scope of the study community and consider contextual factors that can affect decision making.

Computer science collaborators (i.e., AI modellers) should consider themselves as part of the food security project rather than just technical support or information technology consultants. They can also build a common vocabulary while explicitly exploring food security problems to help understand the contexts of study communities.

Researchers may create a culture of listening and open communication with stakeholders and ensure that modelling research provides the results to study communities. A lack of familiarity with research goals and modelling approaches may lead to a misunderstanding of the constraints associated with the application of AI models for food security. Therefore, the organisation of frequent meetings between modellers, researchers, and study communities can help overcome language barriers and provide real-time clarification of jargon or misunderstandings.

AI modellers can also engage with study communities early in the research design process to understand local needs and explain any limitations that cannot be met in the modelling research.

The provision of training and capacity building to researchers from different disciplines and stakeholders on basic quantitative skills, computational literacy, and scenario building can aid in the interpretation of research results, integration into policy, and other aspects of the research process. This can help study communities better understand model outcomes and enable modellers/researchers to communicate research goals for improved collaboration and communication.

Researchers can also help stakeholders develop Decision Support System (DSS) tools to enable feedback provision and advisories to communities facing food security challenges. The communication of the research outcome to stakeholders and study communities can also be carried out through various knowledge products, such as computer-based data visualisation tools or by linking modelling outcomes to mobile devices and apps.

Research funders should also ensure the provision of feedback and/or the implementation of findings to stakeholders or study communities as part of the funding requirement. Assessments of research proposals requiring funding should integrate the aforementioned criteria as components. The monitoring and evaluation of research should also ensure that researchers are in contact with stakeholders and study communities. Funding mechanisms are needed to support integration, continuity, shared learning, and continuous innovation.

Future Research

While this study provides insights into where and how AI models are applied for food security, there is a limited assessment of the extent (measurable) that the use of Artificial Intelligence helps or can help achieve the required level of food security. The identified limitations of this research are mainly attributed to the literature review approach adopted. Future research should focus on evaluating the continued effectiveness of AI models in improving food availability, accessibility, affordability, and utilisation over extended periods. As food security is influenced by evolving factors, such as climate change, socioeconomic shifts, and global crises (e.g., pandemics), future research should assess how AI models adapt to changing conditions and contribute to the resilience of food systems. Research should delve deeper into the participatory processes involving stakeholders in AI modelling. Understanding how local communities are empowered to make informed decisions and implement AI-driven recommendations can provide valuable insights. Given the diverse geographical locations where AI models are applied, future research should explore the cultural, contextual, and governance factors that influence the success or challenges of AI interventions in different regions. Comparative studies can also be conducted across countries and regions to identify the best practices, the lessons learned, and transferable AI-based approaches for enhancing food security. Future research should also investigate the ethical implications of AI models in food security that involve stakeholders, especially issues related to data privacy, fairness, and the equitable distribution of benefits. Research should also assess the potential unintended consequences of AI-driven decisions on vulnerable populations, including examining the role of policies, regulations, and governance structures in supporting or hindering the implementation of AI models in food security initiatives. Future research should also evaluate the scalability and replicability of successful AI-driven interventions, considering the feasibility of adapting these models to diverse food security contexts. Addressing these research gaps will provide a more holistic understanding of the role of AI in sustainable food security and inform the development of effective, context-specific strategies for enhancing food security worldwide.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agriculture13102037/s1, File S1: Query search applied in the google search engine; File S2: List of funding organisations that sponsored AI-based analytical research; File S3: Type of data applied in approach two.

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